Classification of Sleep Staging For Narcolepsy Assistive Device

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Signature

Shuo Zhang

Abstract

Narcolepsy is a chronic neurological disorder caused by the brain's inability to regulate sleep wake cycles normally [1]. Narcoleptic patients feel overwhelmingly tired and sleepy. They do not have the ability to carry out normal day time activities, such as work or study, hence proper treatment is essential. In order to provide an accurate diagnosis of the sleep disorder, physicians must analyze the sleep stages of the patient.

Sleep staging analysis is the process of extracting sleep information with brain signals known as electrophysiological signals. There are three major electrophysiological signals: Electroencephalograms (EEG), Electro-oculograms (EOG), and Electromyograms (EMG). Through the three signals, physicians and technicians can classify the sleep stages. Although all three signals are important, most physicians and researchers agree that 95% of information can be extracted from EEG signal.

With the current technology, patients must go to the hospital and sleep there over night to perform the sleep stage studies. Electrodes are placed on their scalp, eyelids and skin for this examination. Often patients feel that it is very inconvenient and time consuming. Moreover, the technicians are prone to make human errors during the classification of the sleep stages. These errors are a result of fatigue that the technicians experience while doing the long process of classification of the sleep stages, and the complexity and ambiguity of the rules to determine the sleep stages.

Our research group has worked together to construct a portable device that will provide advice to the narcolepsy patient for activity planning and medication dosage. In addition, it provides fore-warning to the patients prior to an narcoleptic attack. This device will also perform real-time sleep analysis and alertness assessment through processing of electroencephalogram (EEG) signal.

The classification accuracy is extremely important to the development of this device. With high accuracy of the classifier, treatment for the patients can be determined more accurately by the physicians. As a result, the main purpose of the research presented in this thesis is to analyze different classification methodology and to optimize the parameters of each technology to obtain the optimal sleep stage classification results. The thesis will also present the description of the portable device and its components used for the development of the prototype.

Acknowledgements

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Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Motivation

Sleeping is very important for a person's well being and health. Sleep deprivation can cause personal discomfort and unhappiness. Personal discomforts such as loss of self-esteem, lack of social ability, and depression all can add up, and cause huge problems in people's daily lives. In order to improve the lifestyle of such people, physicians have done extensive research to cure or treat this problem. Through examining the quality of the sleep, a method of treatment is developed. The method of studying a patient's quality of sleep is known as polysomnogram. It analyzes the sleep cycle and stages through continuous recording of brain waves, eye movement and muscle activities. In order to perform the test, patients must go to the hospital and sleep there over night. Electrodes are placed on their scalp, eyelids and skin for this test.

This study requires a large amount of time. Also, many patients find it uncomfortable, and inconvenient. Moreover, human technicians are prone to make mistakes doing these long and tiresome tests when analyzing the results for the patients. Achieving 90% accuracy by human technicians in the sleep stage classification is considered to be extremely good result. A proposed solution is to provide an assistive technological treatment for the patient in the form of a portable device. This device, designed specifically for narcoleptic patients, will perform real-time sleep analysis and alertness assessment through processing of electroencephalogram (EEG) signal. This device is called the Narcolepsy Assistive Device. The main goal for the Narcolepsy Assistive device is to aid the integration of Narcoleptic patients to normal society. It will provide advice for activity planning. In addition, it provides fore-warning to the patients prior to an narcoleptic attack.

Classification of the sleep staging is a major part of the assessment done by the device. With accurate sleep staging classification results, medical experts can accurately conclude treatment techniques for the patients.

Therefore, the main purpose of the research presented in this thesis is to analyze different classification methodology and to optimize the parameters of each technology to obtain the optimal sleep stage classification results. Three main classification methodology have been analyzed; Linear Vector Quantization, Probabilistic Neural Network and Feed-forward Neural Network. Cross-Validation method (Jack-Knifing) is applied to validate the classification results. Obviously, the research will also involve feature extraction of EEG signal. In order to perform successful classification, key features must be extracted from the EEG signal. (Note that the feature extraction of the signal is not the focus of the thesis.) Therefore, feature extraction methods will also be discussed briefly in the thesis. In addition, the thesis will present the description of the portable device and its components used for the development of the prototype.

With the optimization of Artificial Neural Networks in place, the development of Detective and Predictive model can be completed. With the completion of these models, the Narcolepsy Assistive Device would be able to perform its major functions effectively.

1.2 Scope and Thesis Organization

The theory of sleep staging and background information of electrophysiological signals is introduced in Chapter 1 and Chapter 2. Motivation for the thesis is also discussed in Chapter 1. This is followed by the architecture of the Narcolepsy Assistive Device in Chapter 3. In addition, Chapter 3 includes a discussion of the design of the Digital Signal Processor. The Digital Signal Processor is the key component of the device where complex computation such as feature extraction of EEG signal and classification of sleep stages is done.

Chapter 4 begins with a brief discussion of the feature extraction of EEG signal. In addition, it examines and explains the methodology used for classification. This chapter describes the analysis of three methods of classification, and concludes with Feed Forward Neural Network as the best methodology for classification of EEG signal. Chapter 5 covers the experimental steps taken to improve the classification results. Also, statistical validation methodology is applied to validate the accuracy of the feed forward neural network classifier. Finally, chapter 6 presents the conclusion of the thesis and future work.

The thesis outline is shown in **Figure 1-1.**

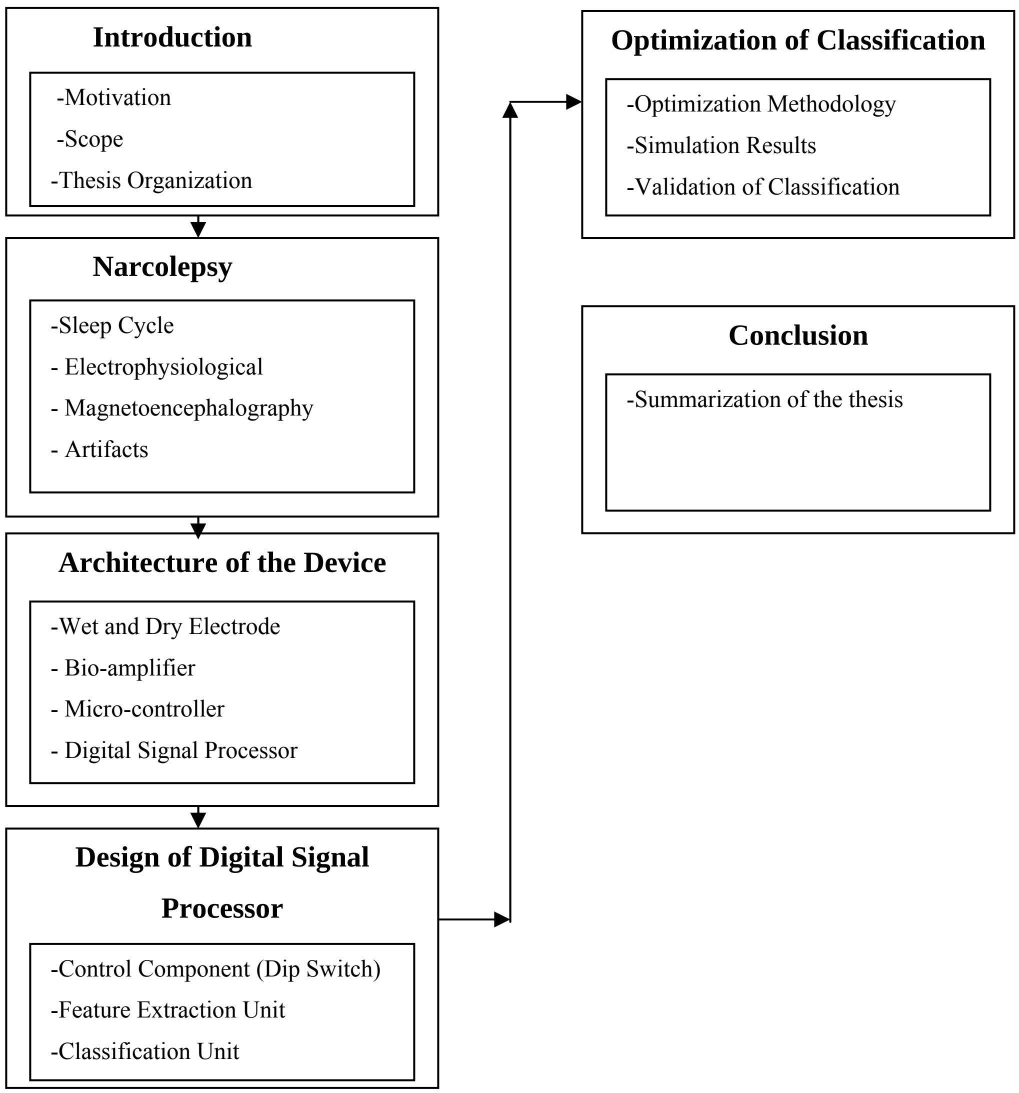


Figure 1-1: Thesis Outline

Chapter 2

Narcolepsy and Sleep Cycle Information

The quality of sleep directly affects the quality of life. One in every two thousand Americans have a sleeping disorder; the most common type of sleep disorder is known as Narcolepsy. Narcolepsy is defined as a chronic neurological disorder caused by the brain's inability to regulate sleep wake cycles normally[2]. This disease causes the patient to feel overwhelmingly tired and sleepy. Patients with this disorder often find themselves weak and may even be in the state of sleep paralysis and cataplexy. This interferes with their normal daytime activities. Narcoleptic individuals are at increased risk for motor vehicle accidents due to sleepiness, as well as occupational, household and smoking accidents[3][4][5]. There is no actual cure for narcolepsy. However, medical therapy can control the symptoms and manage to reduce the intensity and the frequency of occurrences. Researchers around the world are working hard to find a better treatment for this disease.

Table 2-1: Narcolepsy Symptoms

Symptom	Description
Narcoleptic Sleep Attack	Uncontrolled excessive daytime sleepiness
Cataplexy	Loss of Muscular Control
Sleep Paralysis	Muscular paralysis when awakening or falling asleep
Hypnagogic Hallucinations	Vivid dream state usually occurring during sleep paralysis

In short, narcolepsy is a disorder that causes patients to feel excessive daytime sleepiness, cataplexy, sleep paralysis and hypnagogic hallucination. These symptoms prevent the patients of being able to provide key information regarding the progress of the illness to the physicians. Refer to **Table 2-1** for more details of the Narcolepsy Symptoms. As result, the portable assistive device's main objective is to provide first hand information to the physicians. The process of extracting sleep information is known as sleep staging.

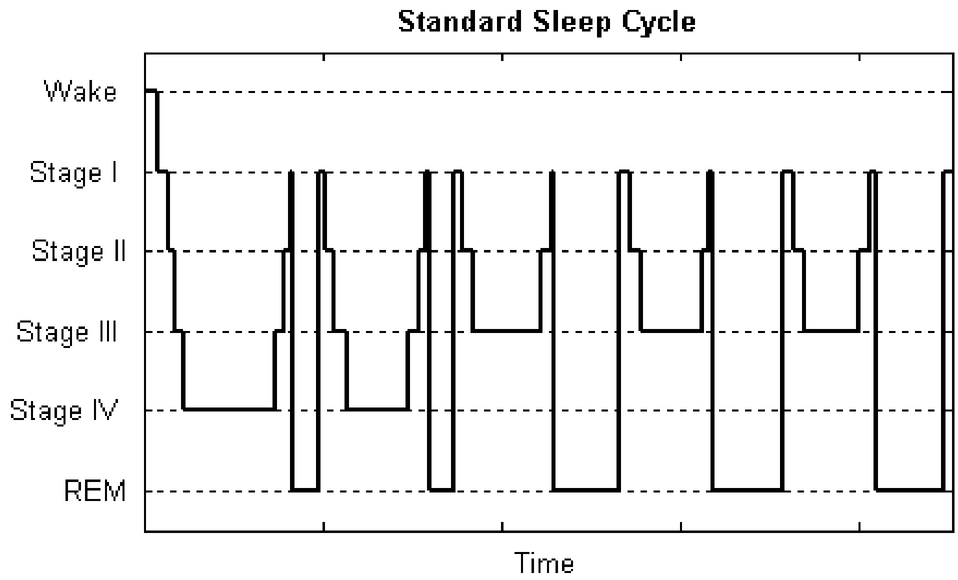


Figure 2-1: Standard Sleeping Cycle [6]

2.1 Sleep Staging

There are two types of sleep stages. One of them is known as Rapid Eye Movement (REM) sleep. During this stage, the person's eyelids move rapidly. Rapid Eye movement usually indicates that the patient is under dream state. It is correlated with a set of physiological activities, which include dreaming, change in heart rate and blood pressure, paralyzed movement and high brain activity. The second type of the sleep stages is Non-rapid Eye Movement (NREM); also known as non-dream state. In most cases, NREM occurs first, and then REM begins. There are four stages in NREM. The first stage is known as the light sleep. This stage lasts only about ten minutes. The second stage is the deeper sleep and last 30 minutes. Stage three is short and only lasts a few minutes. However, the final stage can last up to forty minutes. At the end of sleep stage 4, the REM period begins. The dream state can last five to twenty minutes. In a typical eight-hour night, four or five sleep cycles will occur. Each subsequent cycle lasts longer, as its respective REM stage extends. This effect along with the standard sleep cycle can be seen in **Figure 2-1**.

Past researchers have found that a significant amount of narcolepsy patients have a history of severe night-time sleep disturbance. Therefore, a possible treatment is regularizing the sleep at night for the patients to reduce the number of narcoleptic attack incidences during daytime. As a result, by conducting a study of sleep stages, the physicians can more accurately come up with treatment techniques for the patients.

2.2 Electrophysiological Signals

Sleep staging can be defined as a process to extract features from the electrophysiological signals. Electrophysiological signals are used to extract features for the classification of sleep stages. There are three major electrophysiological signals: electroencephalogram (EEG), electromyogram (EMG), and electrooculogram (EOG).

Electroencephalogram is a set of signals measured with electrodes on the scalp. It measures the electrical activity of the brain. It varies according to sleep state level and mental activity. When there is an interaction between the cortex and the deeper brain structures, electric potentials are generated and recorded as EEG signals. The measurement of EEG signals is done through measuring the relative difference in potential between two electrodes where one electrode is negative and the other is positive.

The second most important electrophysiological signal is the electromyogram signal. This signal measures the electrical activity of the muscles. It was found that during sleep, muscle activity decreases. In order to receive an EMG signal, a needle electrode is inserted through the skin into the muscle. The electrical activity detected by this electrode is displayed on an oscilloscope and may be heard through a speaker [7].

Finally, electro-oculogram is the recording of voltage changes caused by eyeball movement. This voltage potential can be measured by electrodes placed on the skin on either side of the eye. During eye movement, the cornea moves towards one side of the electrode while the fundus moves away. The movement results in a potential difference. When the eye is not moving, the relative change is zero. Moving the eyes slowly can be recorded as a smooth wave, while moving the eyes rapidly will result in sharp curves on the wave of electro-oculogram signals.

Though, all three electrophysiological are useful for the classification of sleep stages, most researchers agree that the majority of sleep stage information is extracted from the EEG signal. As a result, the design of narcolepsy assistive device only consists of components for extracting and processing of EEG signal.

2.2.1 Magnetoencephalography

Besides using Electroencephalogram to measure brain activity, Magnetoencephalography (MEG) can also be used. MEG evaluates the activity in the brain through measuring the magnetic field produced by the brain. Using a very sensitive device known as super conducting quantum interface device (SQUID), the magnetic field is measured. Due to the fact that the emitted magnetic field by the brain is in extremely low amplitude (in the order of femtotaslas), recording must take place in the shielding room to shield from external magnetic signals produced by the earth magnetic field. Also, the SQUID can only be operated under extremely low temperature. Due to these constraints, it is concluded it that MEG is not an appropriate method to be used for the Narcolepsy Portable Device. A more desirable method would be using EEG.

2.2.2 The Brain Wave Frequencies

As mentioned earlier, EEG measures the brain activity. Four most common EEG feature waves are alpha, beta, theta, and delta. The classification of the sleep stages is done through the analysis of the four measure waves. The four types of EEG signals are summarized in **Table 2-2.**

Table 2-2: EEG activity Band [8] [9]

Wave	Description
Alpha	-Alpha waves occur at a frequency of 8 to 12 cycles per second in a regular rhythm. - They are present only when you are awake but have your eyes closed - Usually they disappear when you open your eyes or start mentally concentrating. -Amplitude of 20 to 60 μV
Beta	- Beta waves occur at a frequency of 13 to 30 cycles per second. - They are usually associated with anxiety, depression, or the use of sedatives. -Amplitude of 2 to 20 μV
Theta	- Theta waves occur at a frequency of 4 to 7 cycles per second. - drowsiness or slow brain activity -Amplitude of 50 to 75 μV
Delta	-Delta waves occur at a frequency of 0.5 to 3.5 cycles per second -They usually occur when the brain is in deep sleep - Amplitude of 75+ μV

The state of mind of the human brain can be determined with these four characteristic waves. Delta wave has the lowest frequency. It represents that the brain is in deep sleep. Theta wave has a frequency around 4 to 8 Hz. It represents drowsiness or that the brain is in slow activity. Alpha wave is those between 8 to 12 Hz. This wave represent that the human is relaxed but alert. Finally, Beta wave is the highest frequency wave. It has a frequency of 12 Hz and greater. It generally represents that the person is highly alert and focused. These four waves are collectively known as the frequency band activities.

Besides the frequency band activity, there are also transient waveforms. Transient waves are relatively short segments of EEG signal displaying particular patterns. There are three transient waves, sleep spindles, K complexes, and vertex waves. However, they are beyond the scope of this thesis.

2.2.3 Artifacts Affecting EEG

Artifacts can be defined as any electrical potential recording that is not originated from the brain. The source of Artifacts can be divided into three sections; EEG equipment, electrodes, and patients themselves. Electrostatic, electromagnetic interference may occur from the EEG equipments [10]. Artifacts arise at the junction between the electrodes and scalp due to slight displacement of the electrode. Finally, artifacts can also arise from the patient due to eye movement, muscular movement, cardiac action and other movements. The removal of the artifacts is necessary to improve the quality of EEG signal and the accuracy of classification of sleep stages.

2.3 Summary

Narcolepsy is a sleep disorder that affects an individual's daily life. Its main symptoms include day time sleepiness, sleep paralysis, hypnagogic hallucinations and cataplexy. There is no cure for this disorder, however, there are treatments such as stimulants, designed to increase alertness during daytime. In order to find the proper treatment for this disorder, researchers are studying the sleep stages. Sleep staging is a process of extracting sleep information through measurement of brain activity. It can be extracted by two method; Electroencephalography and

Magnetoencephalography. Due to the fact that Magnetoencephalography has certain limitation, Electroencephalogram is a better method to measure brain activity. Also by reducing artifacts, a more accurate result can be measured. With the accurate information extracted from the patient's brain, medical specialists are better able to monitor changes in alertness and determine an appropriate treatment for the patient. In order to extract the information from the patient, a new approach has been constructed. This approach is to utilize a technological solution by designing a device that can analyst the sleep data collected from the patient and perform automated classification of sleep stages.

Chapter 3

Overview of Narcolepsy Assistive Device Design

3.1 Introduction

The Narcolepsy Assistive Device is intended to be a technological cure developed to that facilitates the integration of narcoleptic patients to mainstream society. It is designed to be portable, long term recordable, reliable and cost effective. Therefore, power consumption, size device, and cost are minimized.

The main objective of the device is automated sleep staging classification. With the information collected and processed by the device, physicians can make better judgment for the treatment of the patients.

3.2 Block diagram

The major components of the device are illustrated in **Figure 3-1**. The device consists of electrodes, bio-amplifier, micro-controller, digital signal processor, flash memory and display.

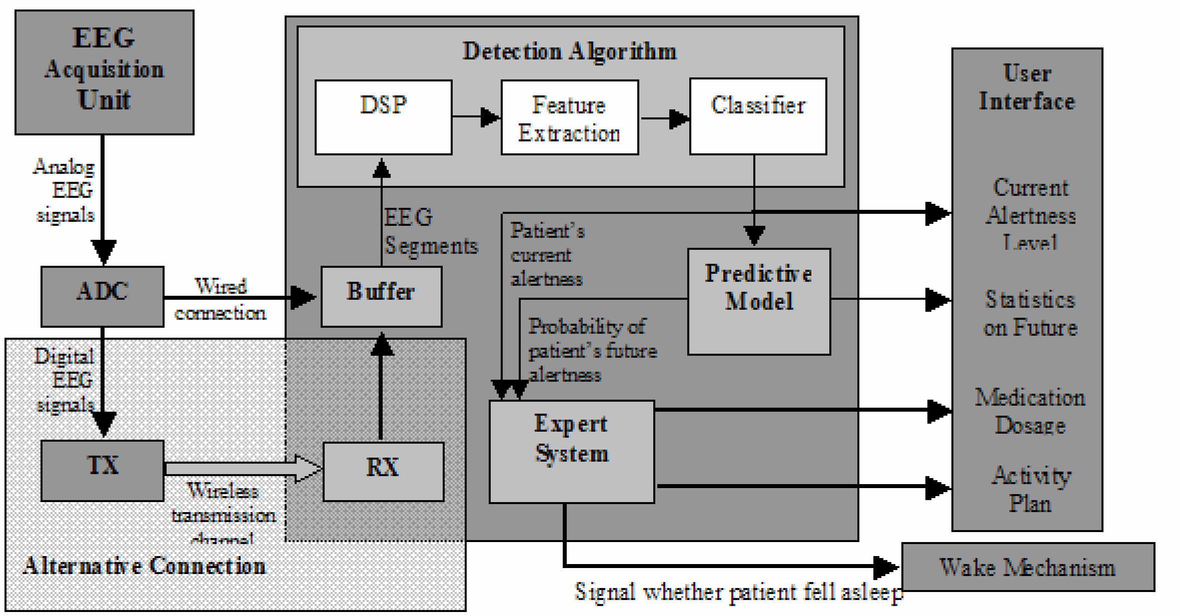


Figure 3-1: Components of Narcolepsy Assistive Device [11]

3.3 Signal flow

EEG stream is captured from two recording spots on the scalp using dry EEG electrodes, then the signals are fed into the signal conditioning circuit where the signals are filtered and then amplified to improve the signal-to-noise ratio. The signal is digitized prior to feeding to the digital section of the system. The first step in the digital signal processing is preparing the data packets where the EEG stream is packed into epochs of 30 seconds. Each packet representing an epoch is the unit of data processing.

The data is then fed into the sleep detection and classification algorithms for further processing. The algorithm processes the data and identifies the current state of the monitored patient and the output is displayed on the LCD screen and in case of a narcolepsy attack, the device will issue an alarm.

3.4 Component Selection

As mentioned in the previous section of the thesis, the Narcolepsy Assistive Device consists of Electrodes, Bio-amplifier, Micro-controller, and Digital signal processor. The device is designed to be portable, long term recordable, reliable and cost effective. As a result, selecting the most appropriate components for the device is crucial.

3.4.1 Wet and Dry Electrode

Electrodes are the sensors that detect EEG signal from the brain. It converts the EEG signal that is normally in the form of ionic current into electric current. In the current technology, there are two main types of electrodes: wet and dry contact electrodes. For wet electrodes, a wet gel is applied to the surface of contact. This gel is an electrolyte made up of chlorine ions. The gel diffuses into the skin to enhance conduction between the metal layer of the electrode and the epidermis layer of the skin. The process of applying the gel can be time consuming and uncomfortable for the patients. Also, the gel dries away in a short period of time. As a result, the conduction between the epidermis layer of the skin and metal layer of the electrode is reduced over time. On the other hand, the dry electrode is a micro array of needles that penetrate through the epidermis layer of the scalp. The needle will penetrate into the stratum germinativum layer where there are cells but no nerves or blood capillaries [12][13]. As result, the needle will not inflict pain or cause bleeding. Dry electrodes also have excellent electrical performance. Since the needles penetrate through the dead skin layer, the conduction has increased significantly, thus noise and artifacts are also minimized. The dry electrodes can be fabricated into extremely small size and can be hidden under the hair.

Through the analysis, it is concluded that dry electrodes are most appropriate for portable devices. (Note, since the dry electrode mentioned above is still in designing stage, it is not available for research usage, as a result, all analysis data used in this thesis is resulted from wet electrode). Below is a summary table that describes wet and dry electrode.

Table 3-1: Wet and Dry Electrode

Wet Electrode	Dry Electrode
Apply wet gel to increase conductivity	No Gel
Large size	Very small
Require skin preparation	No skill preparation
Introduce Artifacts	Reduced noise and artificats

3.4.2 Bio-amplifier

The EEG signal extracted from the electrode has very low amplitude in the range of 10μV to 150μV. Therefore, amplification of the signal is required to improve the signal to noise ratio prior to the processing of the signal. Bio Voltage Amplifier is used for the amplification the EEG signal in the device. Several amplifiers were experimentally compared in terms of noise margin, maximal input impedance and the common mode rejection ratio. With maximal input impedance, it will increase the common mode rejection ratio. As a result, common mode interferences will be rejected. Through the experimentations, instrumentation amplifier has been selected.

The specification of the instrumentation amplifier is shown on **Table 3-2**.

Table 3-2: Features of Amplifier

Features of the Voltage Amplifier
Low Offset Voltage
Low Drift
High Common-Mode Rejection
Wide Supply Range
Input Over-Voltage Protection

3.4.3 Micro-Controller

The micro-controller is control unit of the device that manages system resources and signal flow. Through the experimental analysis, an AVR micro-controller has been selected. The commercial micro-controller selected for the device had integrated LCD driver and Analog to Digital Converter (ADC). In addition, it had surplus peripherals.

However, the micro-controller had a lack of arithmetic processing power. Therefore, a Digital Signal processor is required for the Narcolepsy Assistive Device.

3.4.4 Digital Signal Processor

A digital signal processor (DSP) is a specialized microprocessor designed specifically for digital signal processing, generally in real-time computing. DSPs are created to deal with data streams in real time unlike micro-controllers which are created with advanced interfacing capabilities.

3.5 Summary

One technological solution to prevent accidents caused by narcolepsy attack and provide important sleep stage information to the physicians is by constructing a device that can analyze the sleep data collected from the patient, perform automated classification of sleep stages and set an alarm for the onset of a sleep attack. This device has been designed to be portable, cost effective, reliable and most importantly, accurate classification result. The device is composed of four major parts and has been discussed in this chapter: Electrodes, Bio-Amplifier, Micro-controller and Digital Signal Processor. All classification of sleep stages are done by the digital signal processor. As a result, it is the most important component in the device is the Digital Signal Processor

Chapter 4

Design of Digital Signal Processor

4.1 Introduction

Choosing the competent DSP was constrained by the available processor resources in terms of memory, speed and mathematical performance; as some DSPs are capable of handling floating point arithmetic operation while others can only handle fixed point instructions.

There are three major manufactures that develop DSP: Texas Instruments (TMS320 series), Motorola (DS56800) and Analog Devices (ADSP-21xx series). Those DSPs exhibit different features and benefits and the search is for the most efficient, fastest processor and compatible with Matlab for simulation purposes.

4.2 Choosing a suitable DSP

A competent digital signal processor for the narcolepsy assistive device should be capable to handle mathematical operations of the signal processing algorithms. The processing algorithm includes feature extraction of the EEG signal, and the sleep stage classification. This requires the processor to compute complex mathematical functions including Fast Fourier Transform as well as floating-point arithmetic. The TMS320c6711 Digital Signal Processor is selected for this application exhibiting 32 bit instructions, and 6 ALUs (Floating and Fixed Point) and a Matlab compatible Development Kit.

There are hundreds, perhaps even thousands of different types of Digital Signal Processors on the market. It is a difficult task finding the most suitable DSP for the Narcolepsy Assistive Device. The best way is to setup a constraint table. With this table, the benefits of using TMS320c6711 Digital Signal Processor is shown. Table 4-1 lists the required features of the DSP processor.

Table 4-1: DSP required features

Comparison Criteria	**Details of TMS320c6711**
Cost	Low cost (Less that 500 dollars)
Processing Speed	High throughput to handle the EEG data processing
Accuracy	Able to provide good output range, minimum 16 bit, preferred 32 bit device
Available Complier	Compile C or assembly (compatible with Matlab for simulation purpose)
Have good Development Kit	Development Kit (DSK) is important, should contain both DSP processor, on chip RAM, A/D-D/A and full expansion busses

4.3 Layout of the Digital Signal Processor

TI TMS320 series DSPs exhibited features that satisfy the requirements of this device and a prototype for the device was built and tested using the TMS320C6711 DSP kit. Figure 4-1 represents a block diagram for the signal flow inside the DSP processor. This layout is based on the TI TMS320C6711.

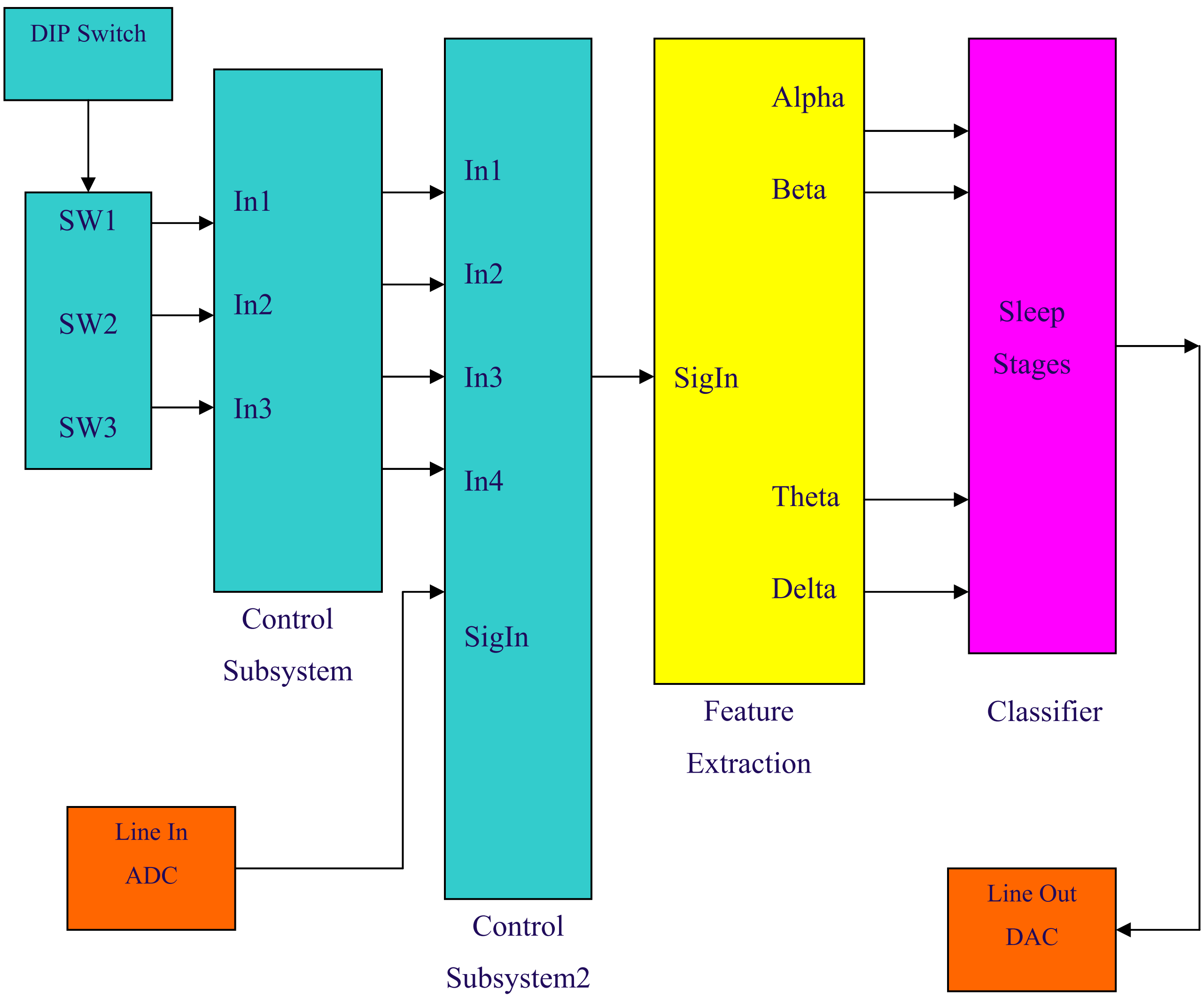


Figure 4-1: Basic Layout of the Digital Signal Processor

The Digital Signal Processor consists of three sections, the Control Unit, Feature Extraction and Classification. The control unit is made up of dipswitches and two control subsystem. Through the switching of the dipswitches, it can activate different functional parts of the digital signal processor. Once the dipswitches activate the control subsystems, the EEG signals are sent, and the feature band waves (alpha, beta, theta and delta) are extracted. The extracted features are then fed into the trained classifier to perform sleep stage classification. Below on **Figure 4-2**, **Figure 4-3** and **Figure 4-4** shows the Dipswitch and the control subsystem 1 and control sub system 2. (Note: the following 3 figures are from Matlab simulator)

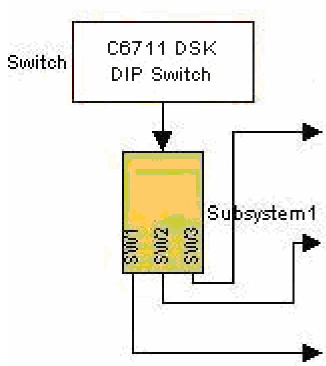


Figure 4-2: Dip Switch

As shown from the figure, there are three switches. These three switches control the Control subsystems.

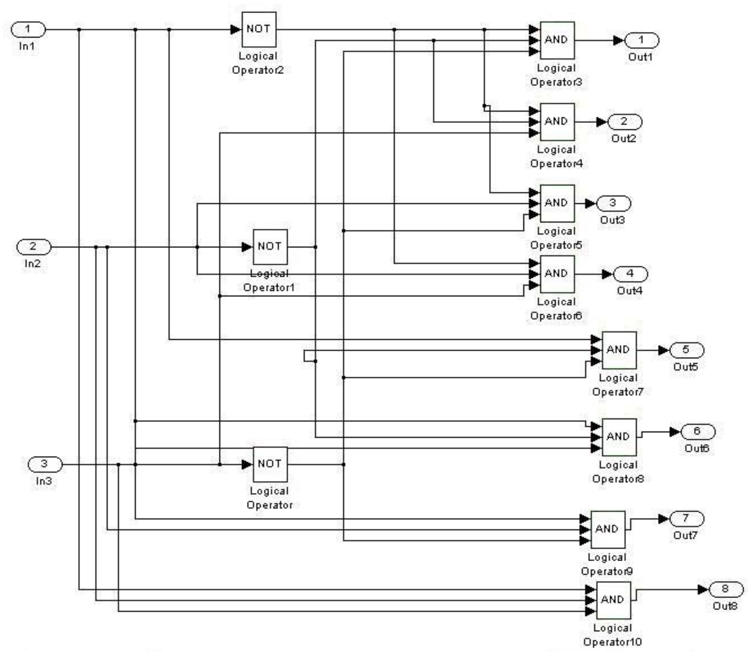


Figure 4-3: Layout of Control SubSystem 1

The control Sub System 1 is a digital circuit made up of And and Not logical functions. The logical functions are interconnected together to produce eight output signals (In this first design of DSP, only one of the eight signal is used.) The signal is sent to control subsystem2 as shown in **Figure 4-4**.

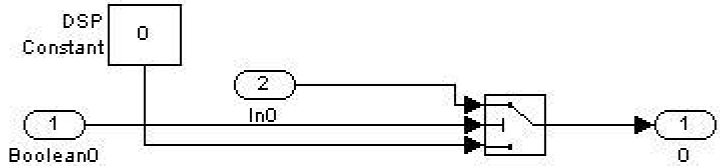


Figure 4-4: Layout of Control SubSystem 2

The Control SubSystem 2's main component is a switch. The switch has three inputs. The switch block sends the first input or the third input based on the valued of the second input known as the control input. The first input is the EEG signal. The third input is a constant value of zero. The second input is the signal from Control Sub System 1. If the signal from Control Sub System 1 sends a digital signal of one, the EEG signal will be sent to the Feature Extraction block. Else, a digital signal of zero will be sent. Once the EEG signal reaches the feature extraction block, four frequency band waves features will be extracted; theta, alpha, beta, delta. (For more information of feature extraction block, please refer to section 5.2.2.) Once the features are extracted, it is passed to the trained classifier.

The classifier is the most important component that can increase the accuracy of the classification of sleep stages. There are many types of classifiers. Considerable work has been done in the selection of methodology of the classification and to improve the accuracy of the classifier. A modern way to do classification is through Artificial Neural Network. More information is presented in the following chapter regarding classification. **Figure 4-5** is an example for the neural network model used in this implementation. The neural network simulated in Digital Signal Processor was selected to be in its simplest form, with one input layer, and one hidden layer. The hidden layer has 10 neurons.

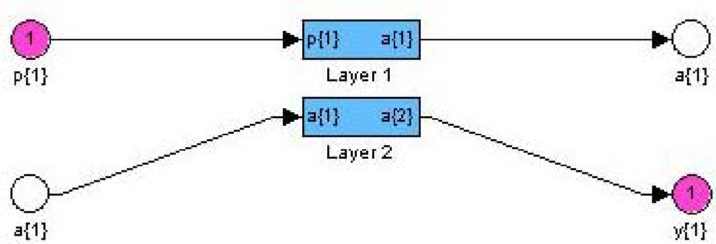


Figure 4-5: neural network model

4.4 Discussion

In today's technology, more and more emerging techniques involving data analysis exist. This encourages improvement in feature extraction methodology. This thesis selected the Continuous Wavelet Transform approach based on literature reviews, not based on simulation analysis. Therefore, more analysis should be done in the feature extraction section. In addition, this thesis has proposed a digital signal processor design with one large classifier that is applied to all patients for classification of sleep stages. Modification can be done to the original digital signal processor design to improve the accuracy of classification as demonstrated in **Figure 4-6.** The data from the patients with sleep disorder can be analyzed by dividing into categories such as male/female, age group, and type of sleep disorder. For each category, one specific trained artificial neural network can be applied. This modification will increase the accuracy of the sleep staging classification significantly.

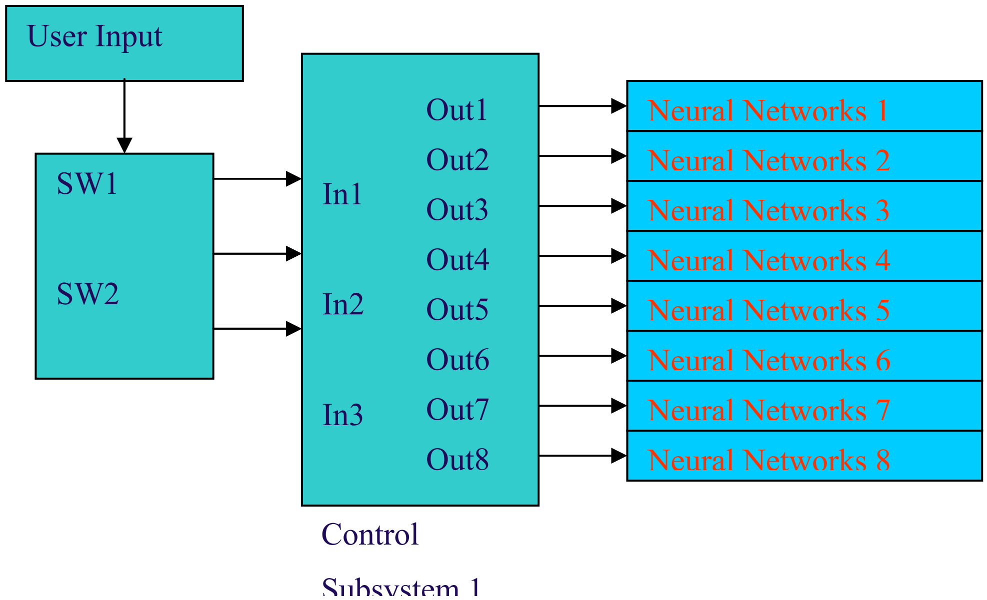


Figure 4-6: Modification Design of Digital Signal Processor

Chapter 5

Classification of EEG Signal by Artificial Neural Networks

With the understanding of Narcolepsy assistive design, it is clear that sleep stage classification is the most influential component for the proper functioning of the device. In previous studies, there have been issues with efficiency and consistency in classification of sleep stages. The following section of the thesis provides introduction and analysis of different Artificial Neural Networks and concludes with best type of Neural Network for sleep stage classification.

5.1 Artificial Neural Networks

5.1.1 Introduction

The Artificial Neural Network is a system that processes patterns. It is inspired based on the way our biological nervous systems process information. It is made up of large number of elements known as the neurons working together to solve complex problems.

Artificial Neural Network work just like human brain. It needs to learn first through examples; training phase. Then, once it is trained, it can solve problems such as pattern recognition, and data classification; classification phase. Neural networks have become increasingly popular with their ability to derive meaning from complex or imprecise data and to extract patterns or detect trends.

They are being applied in many everyday applications such as investment analysis tools; stocks are being predicted based on previous data using neural networks. They are also used in signature analysis. In banks, they are used to compare signatures with those stored in the records.

5.1.2 Background Information

An artificial neural network (ANN) consists of an interconnected group of artificial neurons. Based on a connectionist approach to computation, it uses a mathematical or computational model for information processing. The first fundamental modeling of neural nets was proposed in 1943 by McCulloch and Pitts in terms of a computational model of "nervous activity" [14] [15]. The idea originated from the examination of the central nervous system where neurons along with their different parts (synapses, dendrites and axons), work together to form one of the most significant information processing elements. Even though, neuron itself is a very simple structure element, a large group of such element constitutes a huge amount of processing power.

With 10 billion neurons and 60 trillion connections between them, the human brain can perform its functions way faster than any of the computers that exist today. Research has shown that the brain stores information as patterns. Some of these complicated patterns allow for the identification of individual faces. Complex electrochemical reactions are used to propagate the signals. In response to the stimulation patterns, the neurons are able to form or inhibit the connections and can show changes in the strength of the connections. All these actions form the basis of learning in a brain.

Similar to the real nervous system, an artificial neural network is made up of very simple processors called neurons. These neurons are highly interconnected by weighted links. Each neuron will receive multiple inputs and produce a single output.

Artificial Neural Network is able to use its experiences to train itself. This field of storing information as patterns and then using them to solve problems involves the creation of parallel networks and the training of those networks. When exposed to a sufficient number of samples, ANN can generalize itself to recognize the pattern in the ones it hasn't encountered before. Hence, an ANN can be considered as an abstract simulation of the real nervous system.

Mainly, the neural networks are adjusted such that, a specific input leads to a specific target output. Based on the comparison between the output and the target, the network is adjusted until the network output closely approximates the target. For this purpose, many input/target pairs are used to train a network.

In the analysis of the neural network two different sets of data are required, one for training and one for testing. Training set of data should not be used again as testing set. The reason for that is to ensure that the neural network is learning to predict the pattern and not memorize the original pattern.

5.2 Classification of EEG Signal

5.2.1 Introduction

Traditionally, medical experts perform sleep stage classification manually. To study sleep, it generally requires 8 hours of continuous monitoring and recording of information. This 8-hour data is then broken into 30 seconds segments known as epochs. To analyze the sleep staging, it will require medical experts around 5 hours to process. Thus this process is very time consuming. Also, with continuous monitors, medical experts are prone to make mistakes. As a result, the accuracy could be low. This time consuming process leads to high cost for the health care system. Hence, an automated classifier is required.

Automated sleep staging is aimed to reduce the workload of the technician. It will also increase accuracy and reduce cost. The first step in automated classifier process is feature extraction and selection.

5.2.2 Feature Extraction

In order to classify the sleep stages, features have to be selected and extracted from the Electrophysiological signals. Feature selection and feature extraction are both important stages in sleep stage classification. There are many features that can be used to classify the sleeping stages. Selecting unnecessary features can confuse the classifier and decrease the classification accuracy. Furthermore, extracting extra features will increase the processing time significantly.

The most relevant features for sleep staging classification come from EEG signals. Through the EEG signals, the frequency band waves (theta, alpha, beta, delta) have been extracted.

Table 5-1: Frequency Band

Frequency Band Waves	Frequency Range
Delta	Less than 4 Hz
Theta	4-8 Hz
Alpha	8-12Hz
Beta	12 Hz and more

In order to observe the Frequency Band Waves, EEG signal frequency transformation must be performed. The most common transformation used is the Fourier Transform. Unfortunately, Fast

Fourier Transform calculates the average of the duration of the whole signal, not the transient of the signal. If the transient signal exist in the signal, its contribution to the Fourier transform will be small, and its location on the time-axis will be lost. As result, the Fourier Transform will not yield good results for analyzing non-stationary signals [16]. A better approach is to use the wavelet transformation. This approach can extract information in both short and long time intervals; transient information will not be lost. The simulations shown in this thesis have used Continuous Wavelet Transformation (CWT) approach with Daubechies as the mother wavelet. (It should be noted that Feature selection and feature extraction is not the main focus of the thesis; therefore, the CWT approach is selected based on literature reviews, not based on simulation analysis.)

In order to extract the frequency band wave, the EEG signals are transformed into frequency domain. The features are extracted from the frequency domain. The diagram below shows the process of feature extraction.

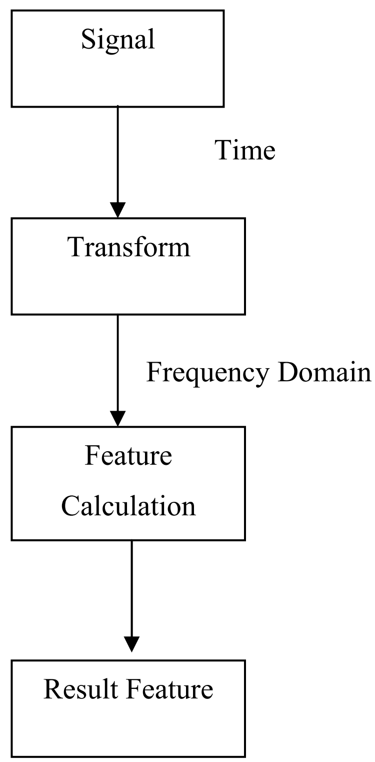


Figure 5-1: Processor of Feature Extraction

The data received from the physician is in the form of magnitude (scale) of voltage potential per second. This data is transformed into frequency values and grouped into a 30 second data epoch. Then, processing each epoch, the actual features are extracted.

Using Matlab, the features have been extracted from the frequency band wave. On **Figure 5-2**, 100 epochs of data are displayed. Each epoch of data contain alpha, beta, theta, and delta feature wave.

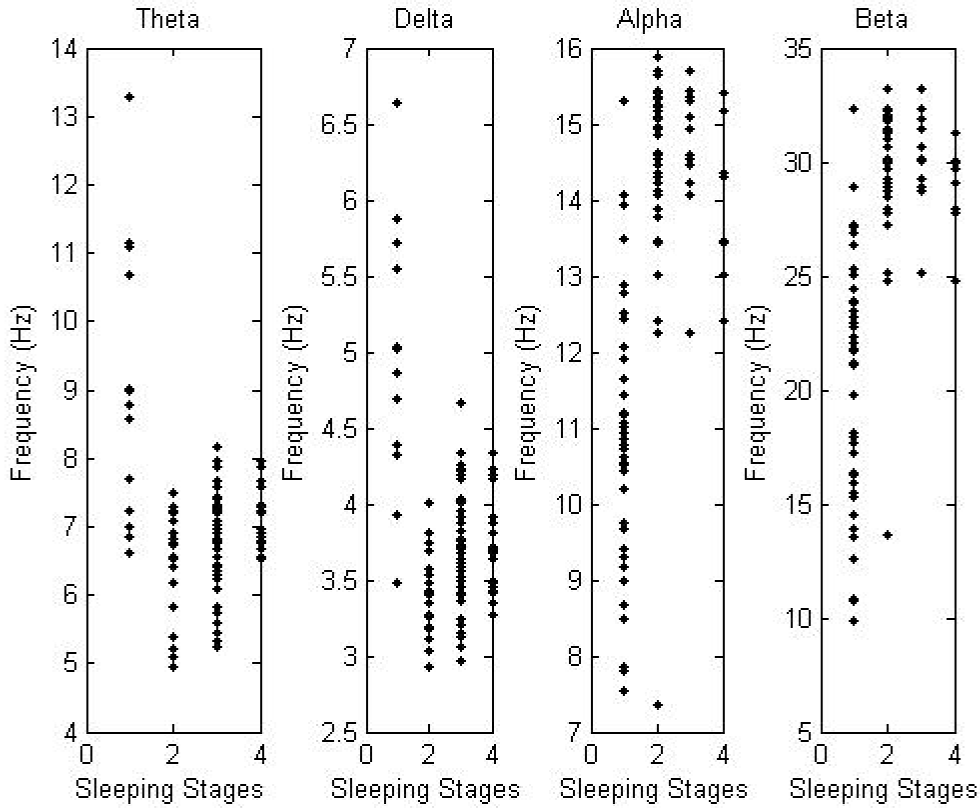


Figure 5-2: Sleep Stages Vs Frequency of Four Feature Waves

As shown from **Figure 5-2**, there are 4 stages: awake (sleep stage 1), sleep stage 2, sleep stage 3, and sleep stage 4. The 100 epochs of data have been used to train the classifiers.

5.2.3 Artificial Neural Network Classifier

Neural networks have found many successful applications in computer vision, signal/image processing, speech/character recognition, expert systems, medical image analysis, remote sensing, robotic processing, industrial inspection, and scientific exploration. Various kinds of network architectures are available and have been trained to perform these complex functions. Most of the applications of these networks can be divided into 5 categories - prediction, classification, data association, data conceptualization and data filtering [17]. Some networks are good for the purpose of one application while others are good for other applications. Therefore, network with optimal design for classification should be selected.

This thesis uses the extracted EEG features for the classification of the sleep stages. Hence, the networks used for classification like Learning Vector Quantization, probabilistic and feed forward network were considered for the purpose of this thesis.

5.2.4 Quantization

This network is based on a Kohonen layer, which is capable of sorting items into categories of similar objects. Learning Vector Quantization is often used for both classification and image segmentation. It maps an n-dimensional space onto an m-dimensional space. However, for complex classification problems where the input vectors are quite close to each other, the network requires a large layer with many processing elements, which is not very efficient. As a result, this method is very slow.

Vector Quantization network contains three layers: input layer, a single Kohonen layer and an output layer. The input layer has one processing element for each input parameter while both the Kohonen layer and output layer are made up of many processing elements. **Figure 5-3** shows the topology of Learning Vector Quantization Network.

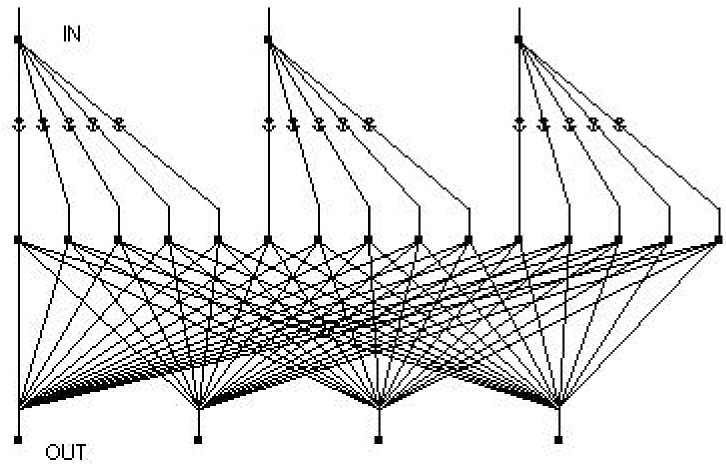


Figure 5-3: Learning Vector Quantization Network

Vector Quantization classifies the input data based on the distance between the input vectors. If the input vectors have data points very close together, they will be grouped as one class. For classification of EEG signals, input vectors are close together even though they belong to different class. Therefore, the accuracy of using the Vector Quantization methodology is low in this particular application. Below is an example that demonstrates the problem with Vector Quantization:

The two input vectors (data received from a 36 years old male patient):

[7.2377 4.3228 8.4974 15.31]

[7.5005 4.0026 9.165 12.621]

The two sets of input vectors are close to each other, hence would be grouped into the same class by this method but they belong to two different stages of sleep, awake and stage 1 respectively. As a result, accuracy of the sleep staging classification is low. Parameters associated with this method have been changed, however, no significant improvement in the accuracy of the classification was observed. Through numerous simulations, the average accuracy of the sleep stage classification was approximately 70%.

5.2.5 Probabilistic Network Analysis

The probabilistic neural network classifier is similar to Bayes classifier, where the class dependent probability density functions are approximated using Parzen estimator. With the estimator, the approach gets closer to the true underlying class density functions as the number of training samples increase, so long as the training set is an adequate representation of the class distinctions [17].

There are three layers after the input for Probabilistic Neural Network. The three layers are pattern layer, summation layer and output layer. However, the pattern layer can be quite large if the categories are less distinct. Moreover, there are few adjusting factors in this approach and therefore, the performance of the network cannot be increased further by changing the parameters.

The analysis process of the Probabilistic Network classifier is divided into two steps. The two steps are the two adjusting factors to increase the accuracy of the classification. The first step is to find the optimal spread value. Through trial and error process, the optimum spread was found to be 0.071. This is proven in the next set of figures.

Figure 5-4 to **Figure 5-8** shows a comparison between the theoretical stage value defined by the doctor and the actual stage value resulted from the classifier. The circle shape represents the stage value defined by the physician. The x shape represents the stage value classified by the neural network classifier. There are 25 epochs of data being tested. Out of the 25 epochs, 7 epochs are for the awake stage, 3 for sleep stage 1, and 15 for sleep stage 2.

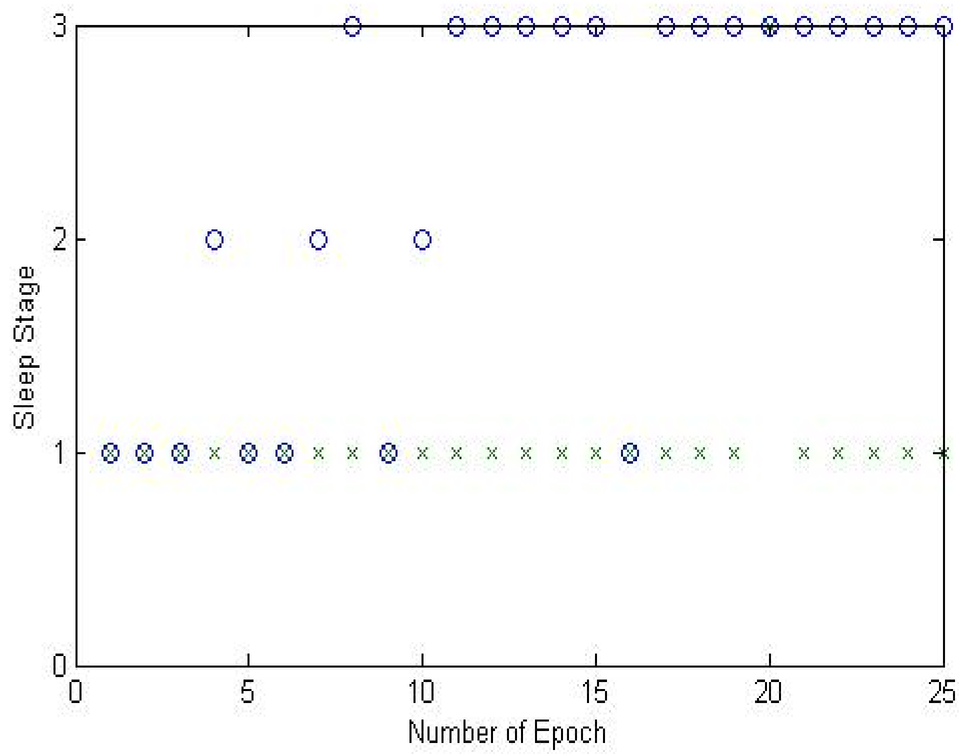


Figure 5-4: Classified results with Spread value of 0.01

In **Figure 5-4** epoch values didn't match. As result, accuracy is only 32 percent.

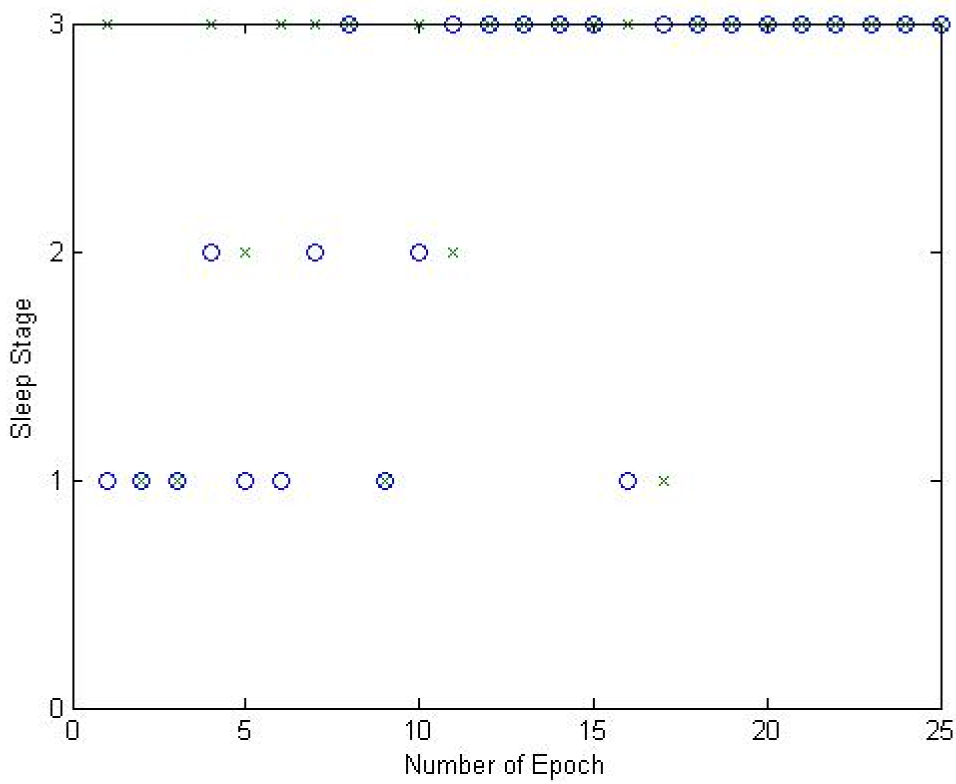


Figure 5-5: Classified results with Spread value of 0.05

In **Figure 5-5**, 8 epoch values didn't match. As result, accuracy is only 62 percent.

However, with the spread value increasing, the accuracy has increased.

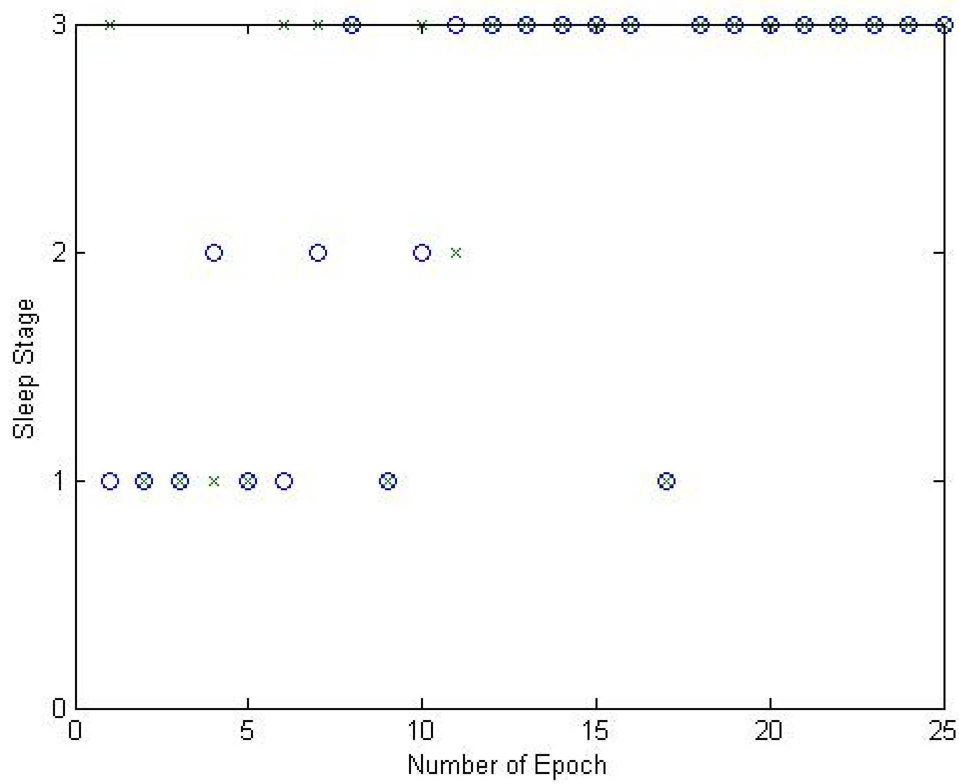


Figure 5-6: Classified results with Spread value of 0.071

In **Figure 5-6**, 6 epoch values didn’t match. As result, accuracy is only 76 percent. At spread value 0.071 the accuracy reaches its peak.

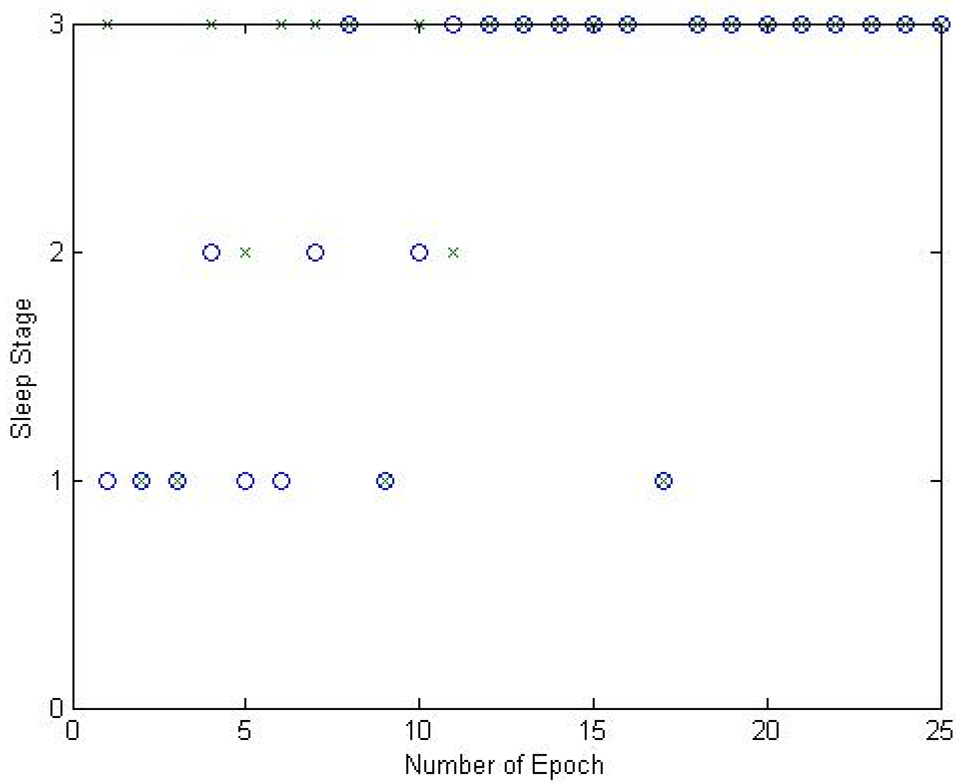


Figure 5-7: Classified results with Spread value of 0.1

In **Figure 5-7**, 7 epoch values didn't match. As result, accuracy is only 72 percent. As spread value increase more, the accuracy has decreased.

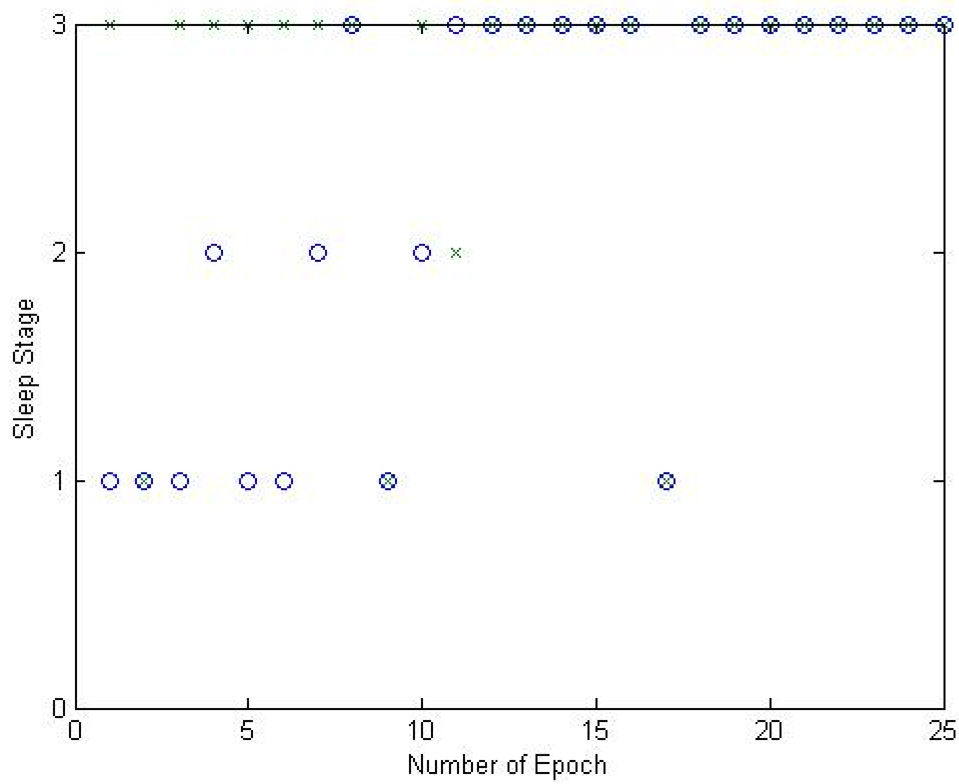


Figure 5-8: Classified results with Spread value of 1

In **Figure 5-8**, 8 epoch values didn't match. As result, accuracy is only 62 percent.

The following graph summarizes the variation of classification accuracy with respect to the spread from this plot. We can conclude that a spread of 0.071 to 0.082 is the best range to receive the most accurate classification result.

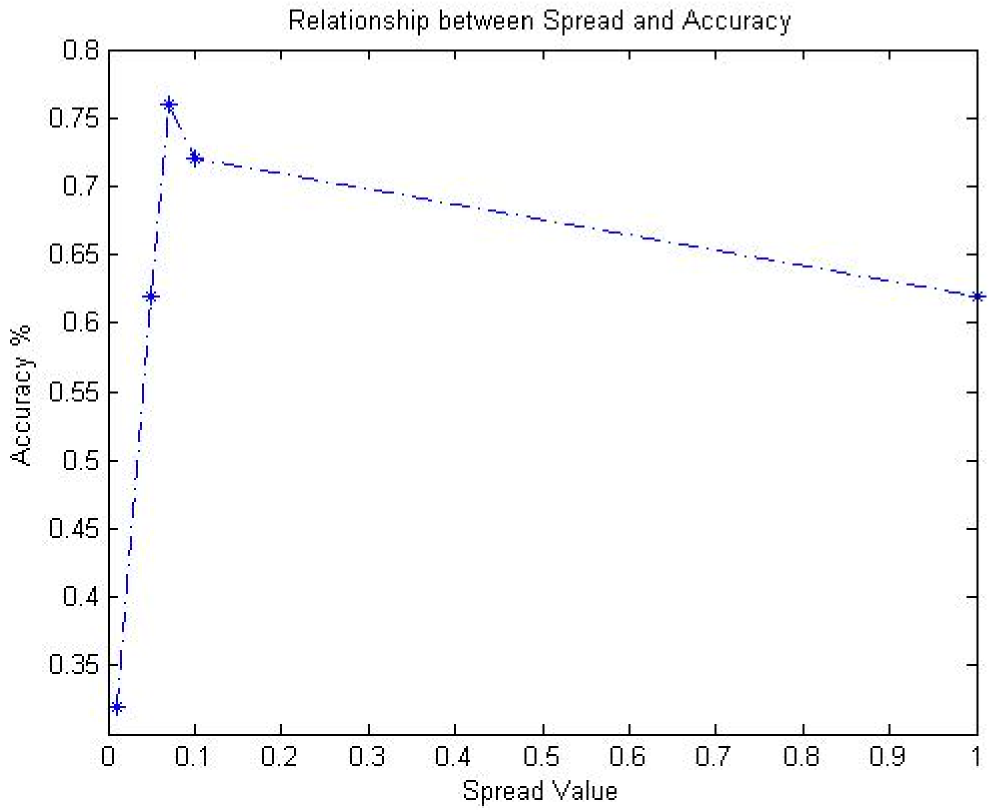


Figure 5-9: Relationship between Spread and Accuracy

Second step in optimizing the classification process is to find a good set of training data. A good set of training data will further increase the accuracy of the classifier.

In this project, a trial-and-error method was used to choose the best training group. The process began by choosing randomly 60 epochs of data as the training set. The optimal accuracy for the 60 epochs of data was 76% as shown in the earlier figures. 30 more epochs of data has been added into the training values. Now, there is 90 epochs in total for training set.

As mentioned in the “feature extraction section” of this chapter, of the 60 epochs of data extracted, there were 10 epochs for wake stage, 4 epochs were for sleep stage 1, 24 epochs for sleep stage 2, and 7 epochs for sleep stage 3. With the addition of the 30 epochs, more epoch data were trained for sleep stage 1 since there were only 4 epochs in the original training data set.

Now, out of 90 training data (epochs), 19 epochs for awake stage, 17 epochs for sleep stage 1, 32 epochs for sleep stage 2, and 7 epochs for sleep stage 3.

Through simulation, results show there is increase in accuracy of the classifier with a better set of training data. For the 90 epochs data set, accuracy of the classifier has improved to 78% instead of 76%. Numerous more simulations have been done, with parameters associated with the method been adjusted, however, no significant improvement in the accuracy of the classification was observed.

5.3 Summary

Linear Vector Quantization algorithm and Probabilistic Neural Network has been utilized for sleep stage classification in this chapter, but they did not result in elevating the accuracy significantly. For Linear Vector Quantization, various drawbacks were found and the accuracy didn’t improve by adjusting various parameters. For Probabilistic Neural Network, the spread value and number of epochs of training data were optimized to obtain the best accuracy of 78%. To achieve a higher accuracy of classification, Feed Forward Neural network has been studied.

Chapter 6

Classification Feed Forward Neural Network

In order to achieve a high accuracy and consistency of sleep stage classification, Feed Forward Neural Network is analyzed in this chapter. Also, various parameters in this network like the number of neurons, the transfer and activation functions have been optimized. This chapter also discusses the optimization of the training set of data and frequency range for the achievement of best results.

6.1 Introduction

A Feed-forward neural network is a multi-layer perceptron with an input layer of source neurons, at least one hidden layer of computational neurons, and an output layer of computational neurons. For more information of the Feed forward neural network, please refer to Appendix A.

6.2 Analysis of the Feed Forward Neural Network

In this project, the analysis for optimizing the accuracy of sleep stage classification involves adjusting the following six main parameters [20]:

- Number of layer in the Artificial Neural Network
- Number of neurons in the hidden layer
- Multiple Activation Functions/Training Functions
- Multiple Learning Functions
- Number of iteration for training epochs
- Frequency range of the sleep stage features (Alpha, Beta, Theta, Delta)

6.2.1 Number of Layers for the Neural Network

For the purpose of the sleep stage classification, the feed forward neural network was selected to be in its simplest form, with one input layer, one hidden layer and one output layer. The hidden layer and output layer have computational neurons. The feed forward neural network was selected with one input layer, one hidden layer and one output layer due to the fact that with the increase of each additional layer will increase the computational complexity exponentially. This means computational time will increase significantly.

6.2.2 Number of Neurons

In each layer of the feed forward neural network there are a number of neurons. However, the number of inputs and output already defines the number of neurons in the input layer and output layer. There are four neurons for the input layer and one neuron for the output layer. Only the hidden layer can be variable. If too many neurons used in that layer, will result in a increase computation complexity and the training set will be memorized. If that happens, prediction of the data will not occur, making the network useless to a new set of data. On the other hand, too few neurons will result with inability to learn or capture the problem. As a result, the optimum number of neurons must be found.

6.2.3 Transfer Functions Used

The key step in optimizing the accuracy of sleep stage classification is to find the optimal transfer function. Four most common transfer functions are shown below in figure:

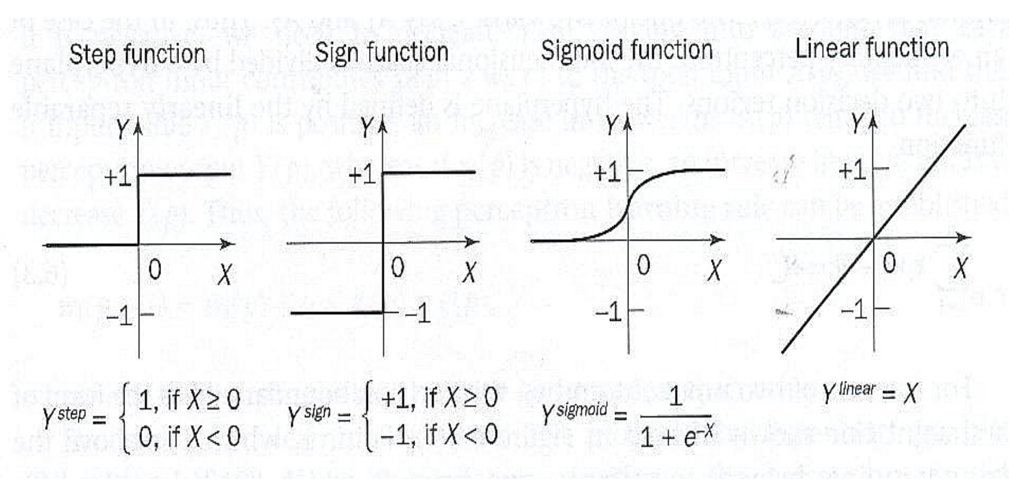
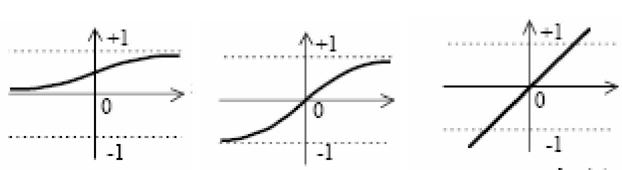


Figure 6-1: Transfer functions of a neuron

As mentioned previously, the feed forward neural network selected for the sleep staging classification has two computational layers: hidden layer and output layer. Therefore, two transfer functions are required. Many combinations of transfer functions were tested, but only two combinations have been found practical: tansig (hidden layer) + purelin (output layer) and logsig (hidden layer) + purelin (output layer). These three transfer functions are shown in **Figure 6-2.**



Logsig Tansig Purelin

Figure 6-2: Transfer Function of Logsig, Tansig and Purelin

All three transfer functions are often used for multi-layered feed forward neural network. As shown in **Figure 6-2,** logsig will produce an output between 0 and 1 as input of the transfer function varies from negative to positive. The output of Tansig is limited between –1 and 1. Only purelin transfer function will produce an output that could be any value. From this observation, it is clear that purelin has to be the transfer function at the output layer since the output of the feedfoward neural network sleep stage classifier could have a result greater than one.

6.2.4 Learning Functions Used

The feed forward neural network learns to perform sleep staging classification through adjusting the weights to reduce the difference between actual and the desired outputs. The initial weight and threshold is initialized randomly, and is then adjusted to obtain the output consistent with the training set of data. To have a more clear view of the classification process, the following table will provide a clear explanation and related equations.

Table 6-1: Learning Function and Equations

Equation	Explanation:
Error(t) = Desired Output(t) – Actual Output(t)	The differenced between the desired output and the actual output is calculated. Depending if the error is positive or negative, the actual output will be adjusted to increase or decrease.
Weight(t+1)=Weight +(learning rate) (input(t)) *(error(t))	The next weight is adjusted based on the current input, the current error, current weight, and learning rate. Learning rate is usually a constant with a value less than one.

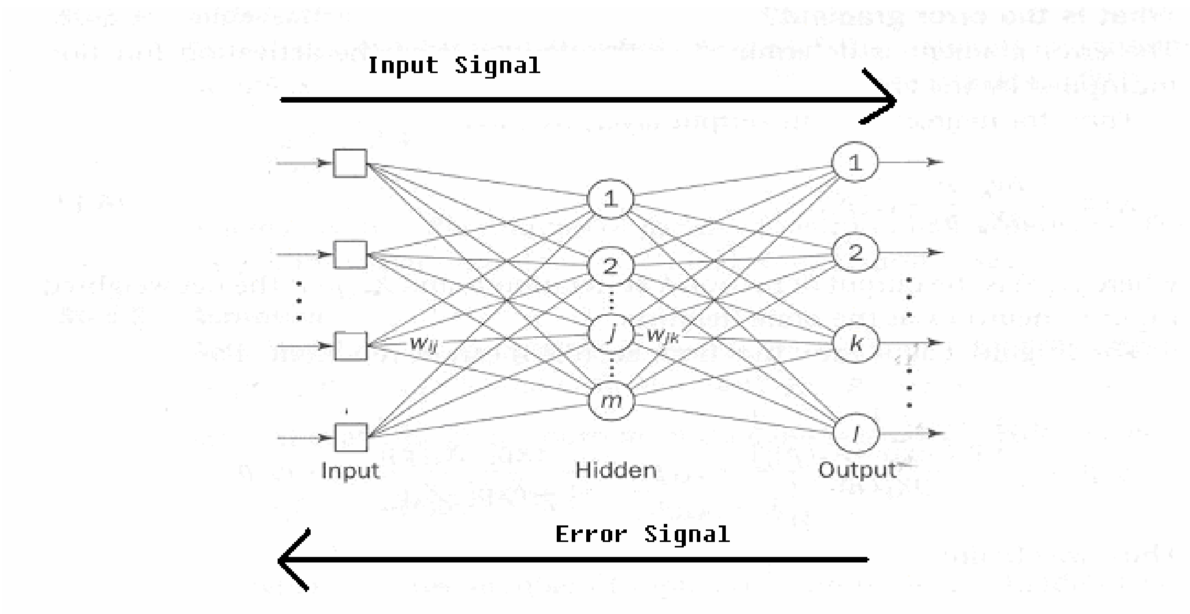


Figure 6-3: **Feed Forward Neural Network**

The feed forward neural network uses the back-propagation learning principle. The calculation of the error signal as shown in **Figure 6-3** above is done from output layer and work backward to the hidden layer. As a result, this learning method is known as back-propagation.

There are many learning functions tested for the classification of sleep stages. **Table 6-2** gives of activation functions used with the matlab command symbol. For more information of each activation function, please refer to Appendix A.

Table 6-2: Activation Functions and Malab Commands

Activation Functions	Matlab Command:
Quasi Newton Algorithm	Trainbfg
Levenberg-Marquardt Backpropagation	*trainlm*
Conjugate gradient backpropagation	*Traincgb*
Resilient Backpropagation	*trainrp*
Scaled conjugate gradient back-propagation	*trainscg*

6.2.5 Change in Distribution of Sleep Stages in the Training Data

Previous Training data began by randomly selecting 100 epochs of data as the training set. **Table 6-3** below shows the distribution of the Sleep Stages in the Training Data.

Table 6-3: Previous Distribution of Training Data

Sleep Stages	Percentage of Training Data of the 100 epochs
Stage 1	13%
Stage 2	6%
Stage 3	55%
Stage 4	15%
Stage 5 (REM)	11%

It is clear from the table, that the sleep stages training data aren't evenly distributed. There is a significant amount of training data for Sleep Stage 3 as compared to the other stages. As a result, the previous training data does not have a good variety of data. Due to this reason, the training data has insufficient information about certain stages and more than enough information about other stages. Hence, the next step is to change the training data such that they represent equal information about all the different stages. This modified data is shown in **Table 6-4**.

Table 6-4: Current Distribution of Data

Sleep Stages	Percentage of Training Data of the 100 epochs
Stage 1	25%
Stage 2	13%
Stage 3	27%
Stage 4	25%
Stage 5 (REM)	11%

6.2.6 Change in Frequency Range

Previously, in the feature extraction section, four major frequency wave bands were extracted from the EEG spectrum; delta alpha, beta, theta. Each frequency band has a defined frequency range. Please refer to table 5-0-5 for the defined frequency range. These four wave bands are the features that make up the training data set for the classifier. Simulations have been run to expand the frequency range of each frequency wave band and using the new frequencies features to train the classifier. However the accuracy of the Feedfoward Neural Network classifier did not increase. The overlap of the ranges may have increased the ambiguity in the training data set. Contracting the frequency bands has also been tested, and no significant effect was seen in the simulation.

6.3 Simulation Results

Following the analysis in the earlier section, feedforward neural network selected for the simulation has only one input layer, one hidden layer and one output layer to reduce computational complexity. For the hidden layer, three different numbers of neuron were used for the simulation. Also five different activation functions have been simulated. In addition, different distribution of simulation data of each sleep stage, and different frequency range for the EEG spectrum all has been tested. The network simulation results are displayed. All simulations results displayed in this section are done with only one hidden layer of neurons. (Note that there is variability in the simulation results due to random initialization of the weights for the network. The results shown below are some typical results achieved.

6.3.1 Change in Learning Functions

Five different learning functions have been simulated with 100 epochs of training data and 100 epochs of testing data. Quasi Newton Algorithm (Trainbfg) is the most appropriate learning function for the classification of EEG signal based on the given set of data. It resulted with the highest accuracy of classification of sleep stage with 73%. This is shown in the following five figures with five different learning functions.

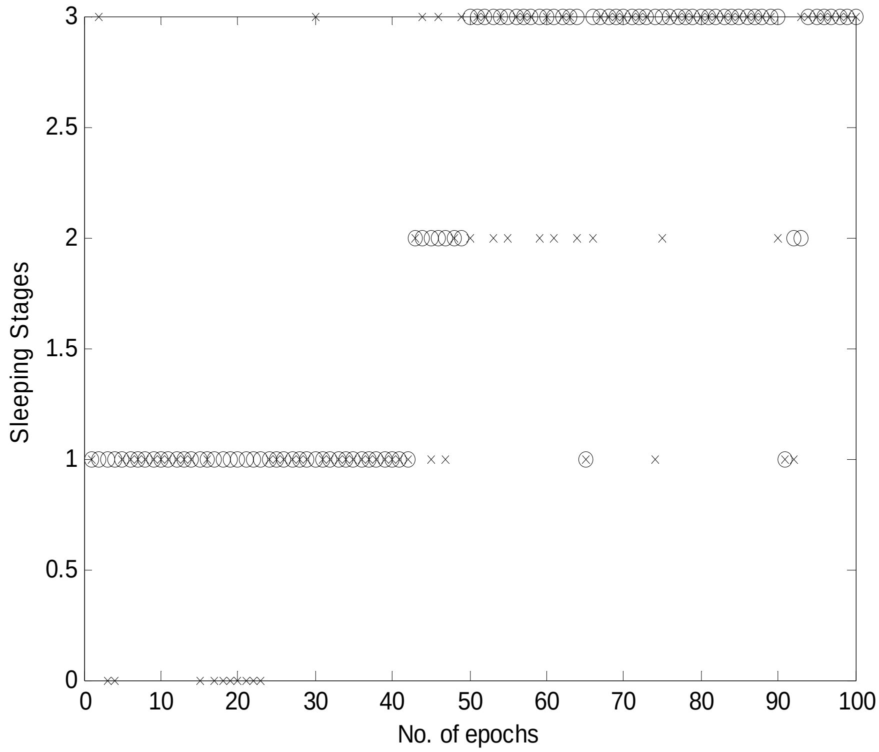


Figure 6-4: **10 neurons, 100 iterations, logsig, trainbfg, 73%, 100 epochs of data set and training set**

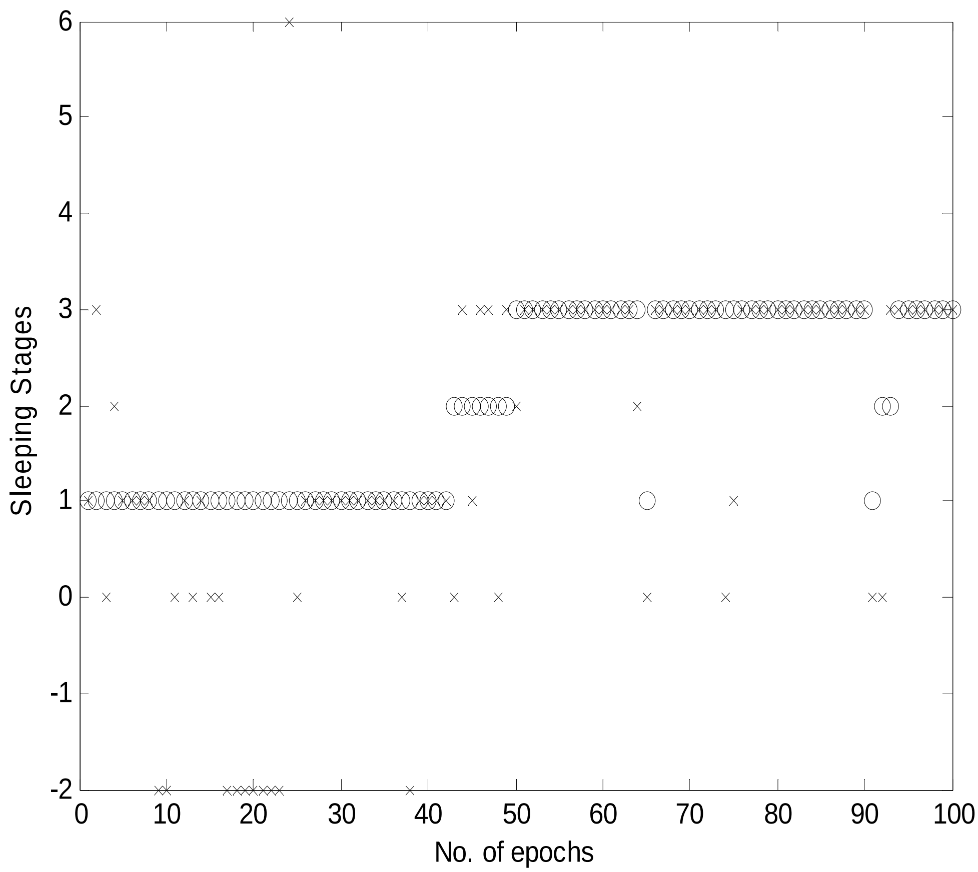


Figure 6-5: 10 neurons, 100 iterations, logsig, *trainlm*, 65%, 100 epochs of data set and training set

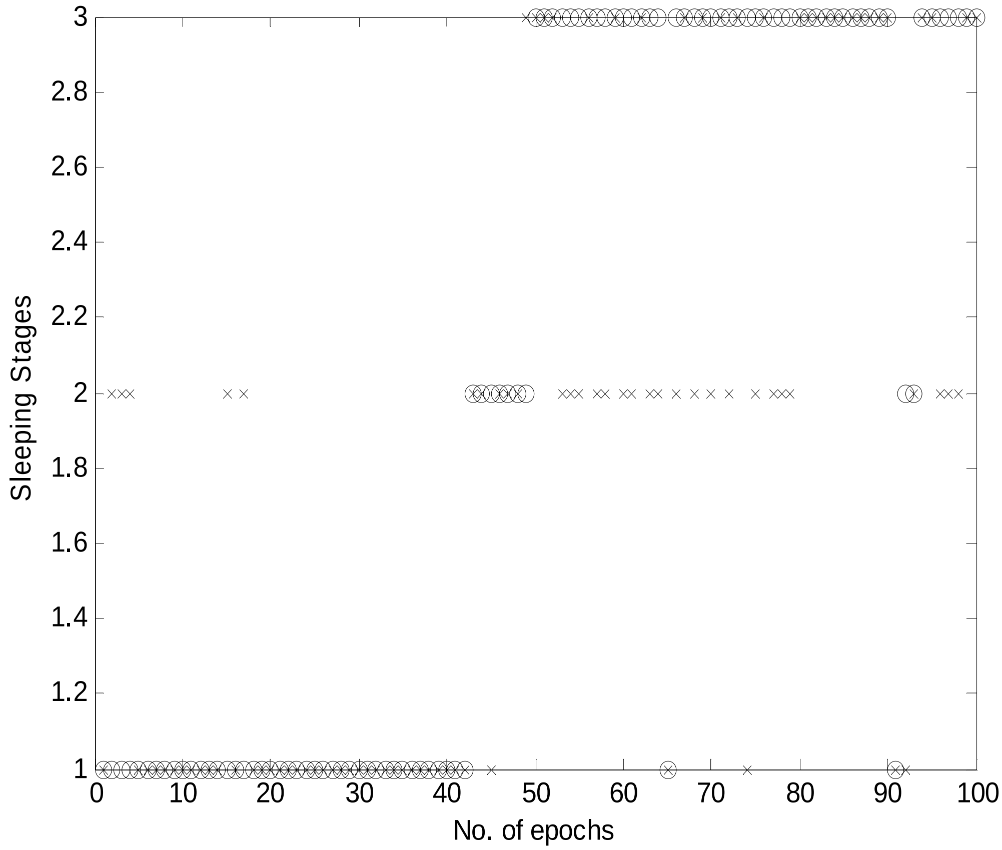


Figure 6-6: **10 neurons, 100 iterations, logsig, traincgb, 71%, 100 epochs of data set and training set**

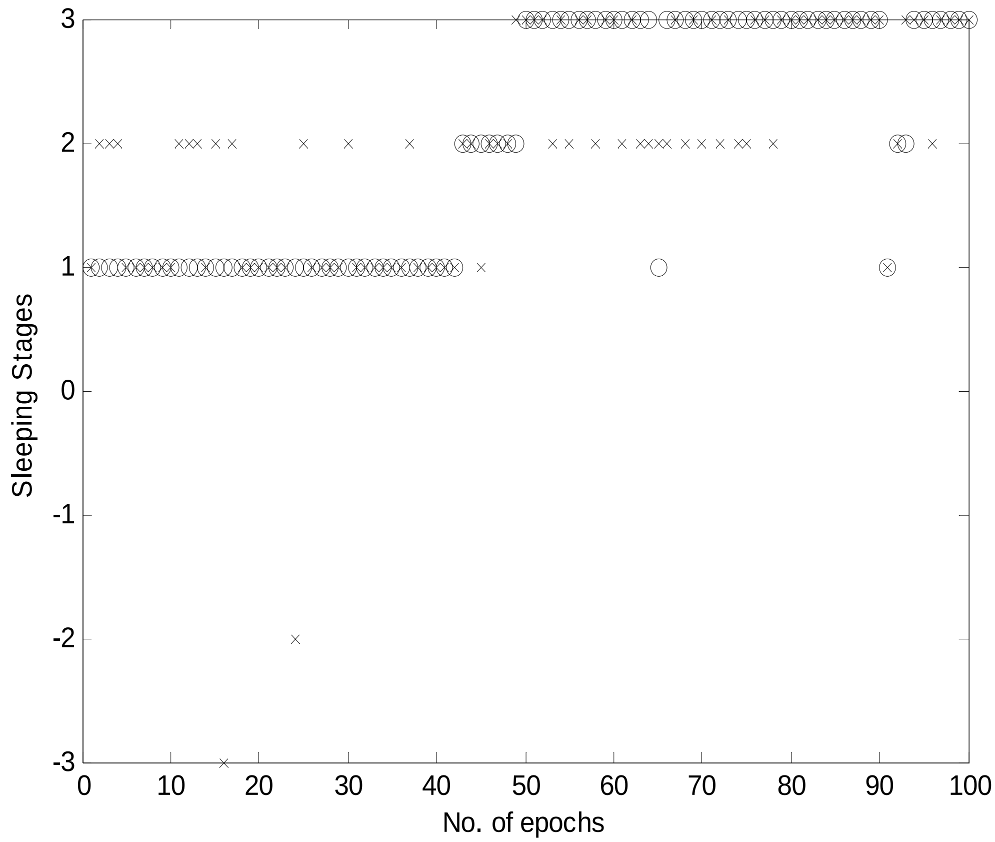


Figure 6-7: 10 neurons, 100 iterations, logsig, *trainrp*, 69%, 100 epochs of data set and training set

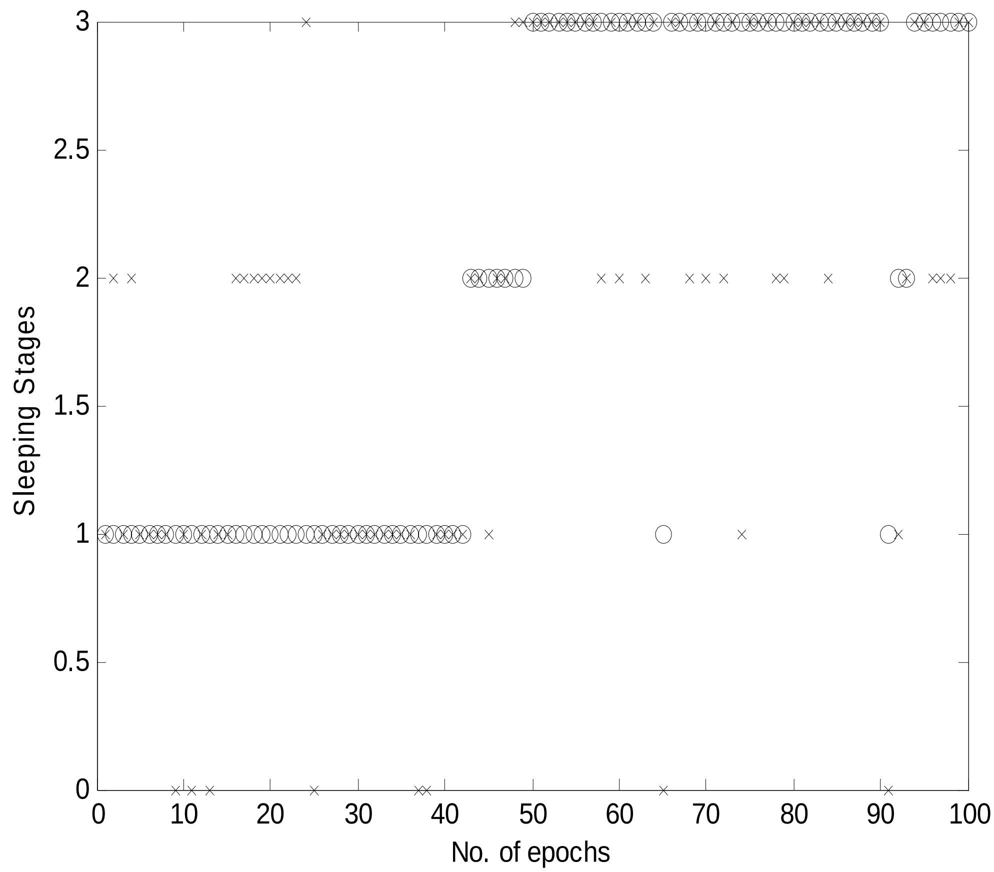


Figure 6-8: 10 neurons, 100 iterations, logsig, *trainscg*, 64%, 100 epochs of data set and training set

6.3.2 Change in Transfer Function

Two different transfer functions have been simulated: logsig and tansig for the hidden layer of the network. There was no significant change in the simulation result. Both transfer function resulted with 73% accuracy with 100 epochs of training data and 100 epochs simulation data. This is shown in the following figure.

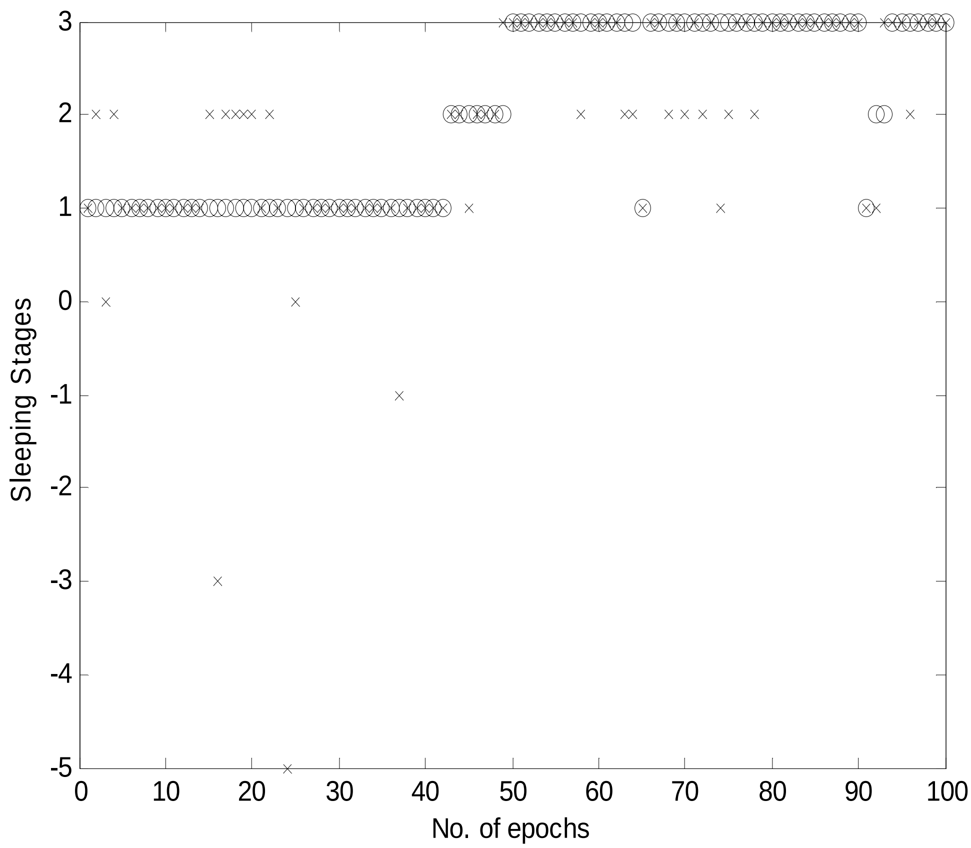


Figure 6-9: 10 neurons, 100 iterations, *tansig/logsig*, trainbfg, 73%, 100 epochs of data set and training set

6.3.3 Change in Number of Neurons in the Hidden Layer

The following three figures show the simulation of 100 epochs of training data and 100 epochs of testing data. The number of neurons of the hidden layer of the Feed Forward Neural Network has been adjusted to find the optimized number. Based it the simulation of the given data, 10 neurons in the hidden layer resulted in with the highest accuracy of 84%.

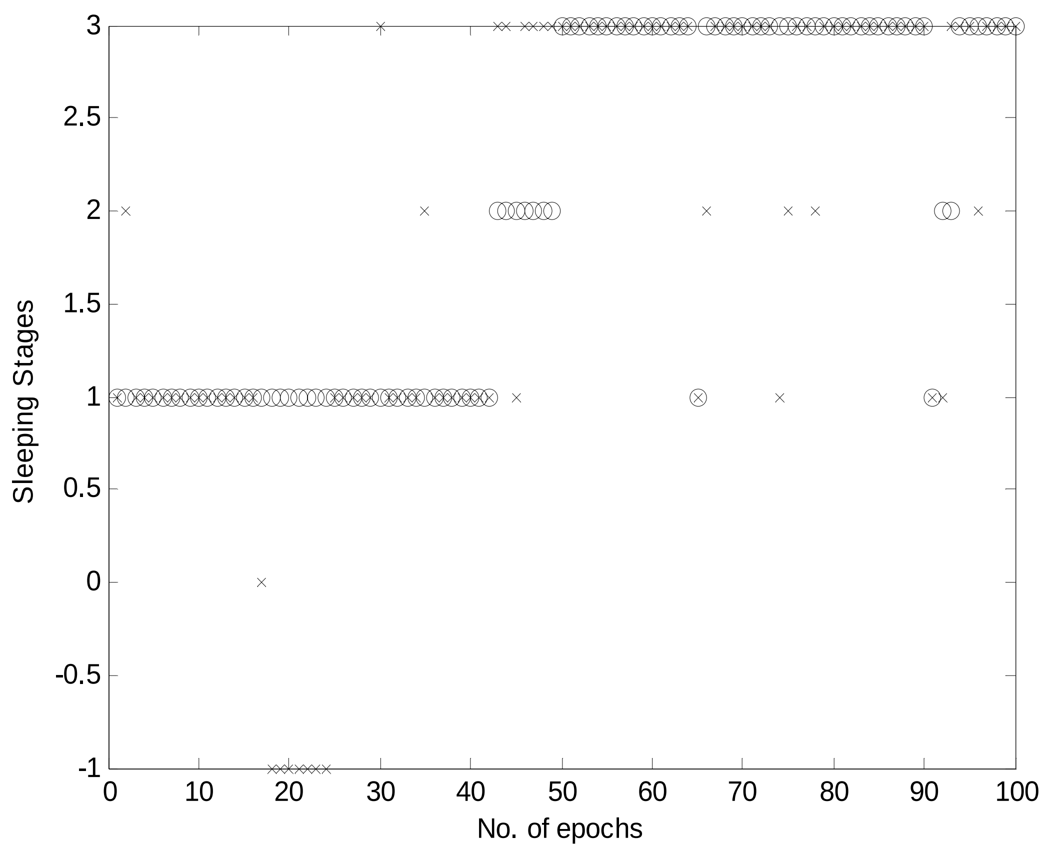


Figure 6-10: 15 neurons, 100 iterations, logsig, trainbfg, 75%, 100 epochs of data set and training set

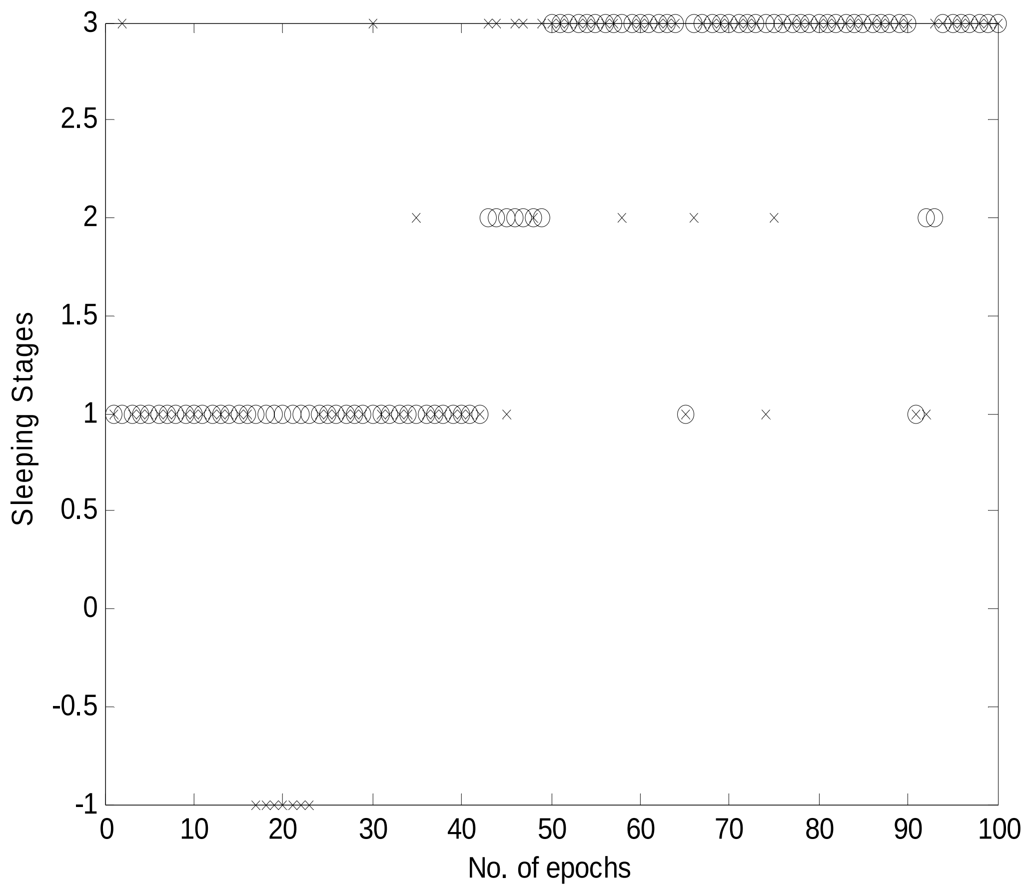


Figure 6-11: 6 neurons, 100 iterations, logsig, trainbfg, 78%, 100 epochs of data set and training set

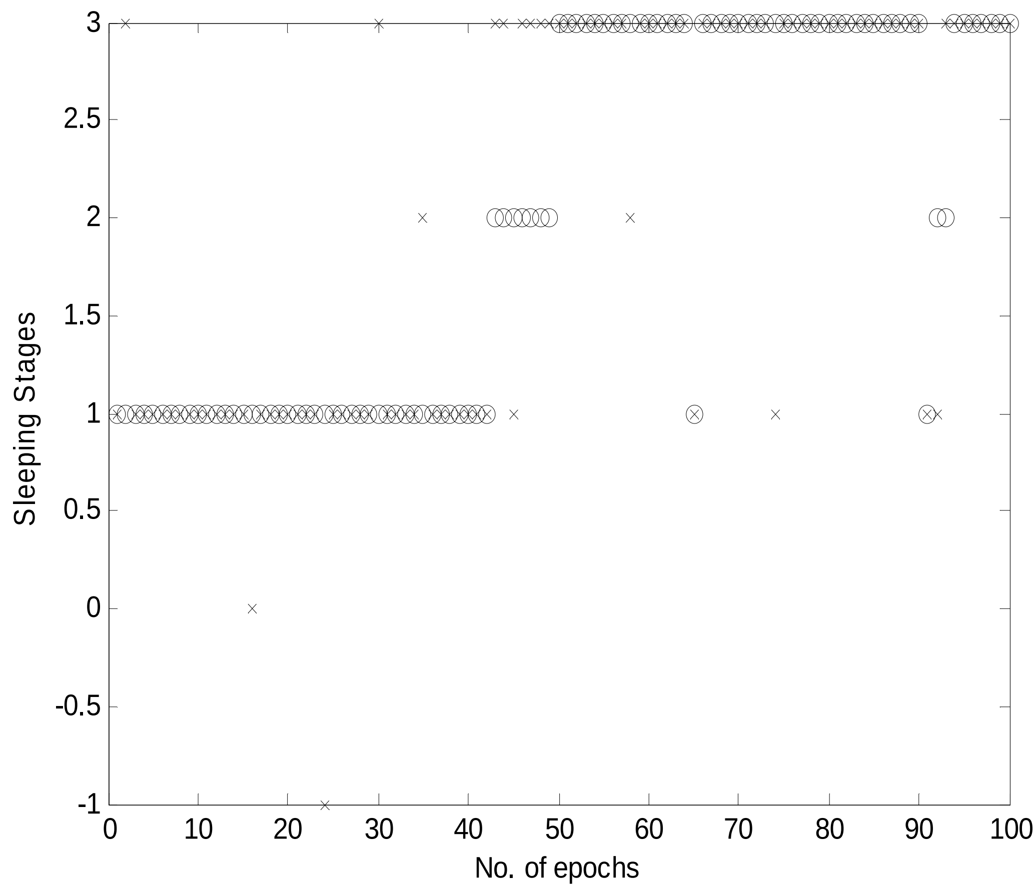


Figure 6-12:10 neurons, 100 iterations, logsig, trainbfg, 84%, 100 epochs of data set and training set

6.3.4 Change in Frequency Ranges

Three sets of frequency range have been simulated as shown in table 6-6. Based on the simulation results, lower the frequency range or increase the frequency range did not increase the classification accuracy for the given simulation data. Previous frequency resulted in the highest accuracy.

Table 6-6: Frequency ranges used for the feature extraction of the EEG signal

Frequency Range For the Features	Delta; Theta; Alpha; Beta;
Previous frequency range	[0 4; 4 8; 8 12; 12 40]
Lower frequency range	[0 3; 4 7; 8 11; 12 38]
Higher frequency range	[0 5; 4 10; 9 13; 11 43]

6.3.5 Change in Distribution of Sleep Stages in the Training

Two sets of training data have been simulated as shown in Table 6-7. Previous simulation data did not have a uniform distribution in the training set unlike the new set of distribution. Using the new set of distribution of data resulted in a higher accuracy of classification as shown in the figures 6-12 and 6-13. The new distribution of training data resulted in a classification accuracy of 89%.

Table 6-7: Distribution of Data

Previous distribution of data		New distribution of data	
stage 1	13%	stage 1	25%
stage 2	6%	stage 2	13%
stage 3	55%	stage 3	27%
stage 4	15%	stage 4	25%
stage 5	11%	stage 5	11%

Below shows the best result obtained with the previous distribution of data:

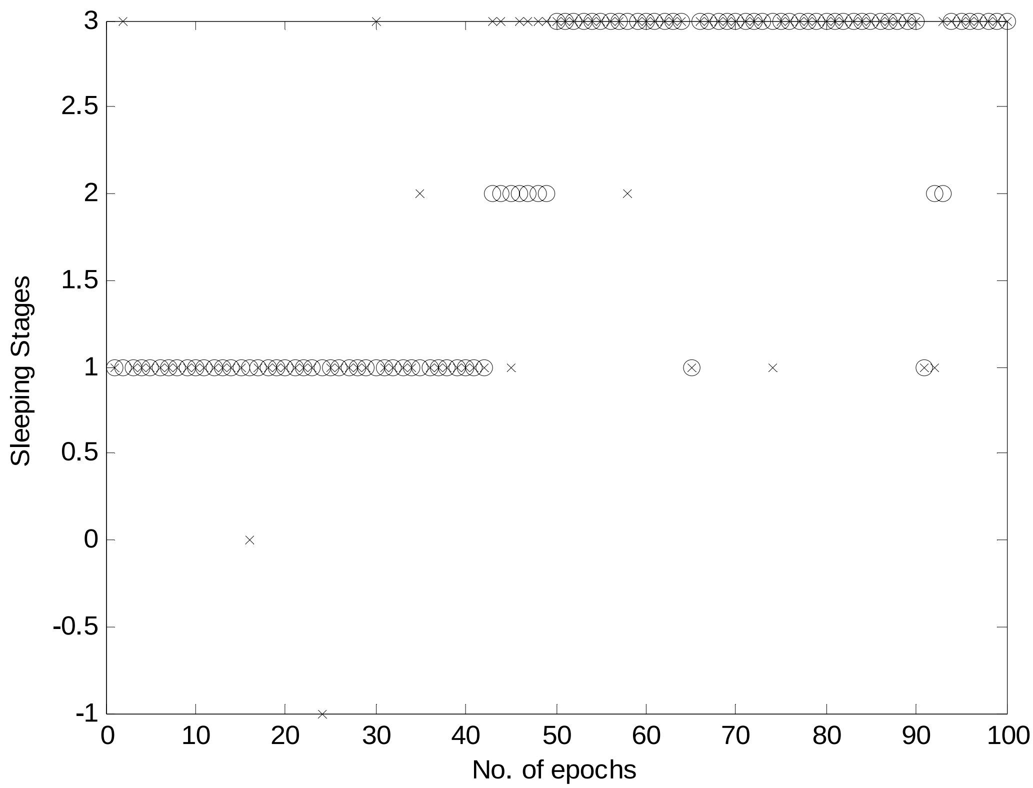


Figure 6-13: 10 neurons, 100 iterations, logsig, trainbfg, 84%, 100 epochs of data set and training set

Below shows the best result obtained with the new distribution of data:

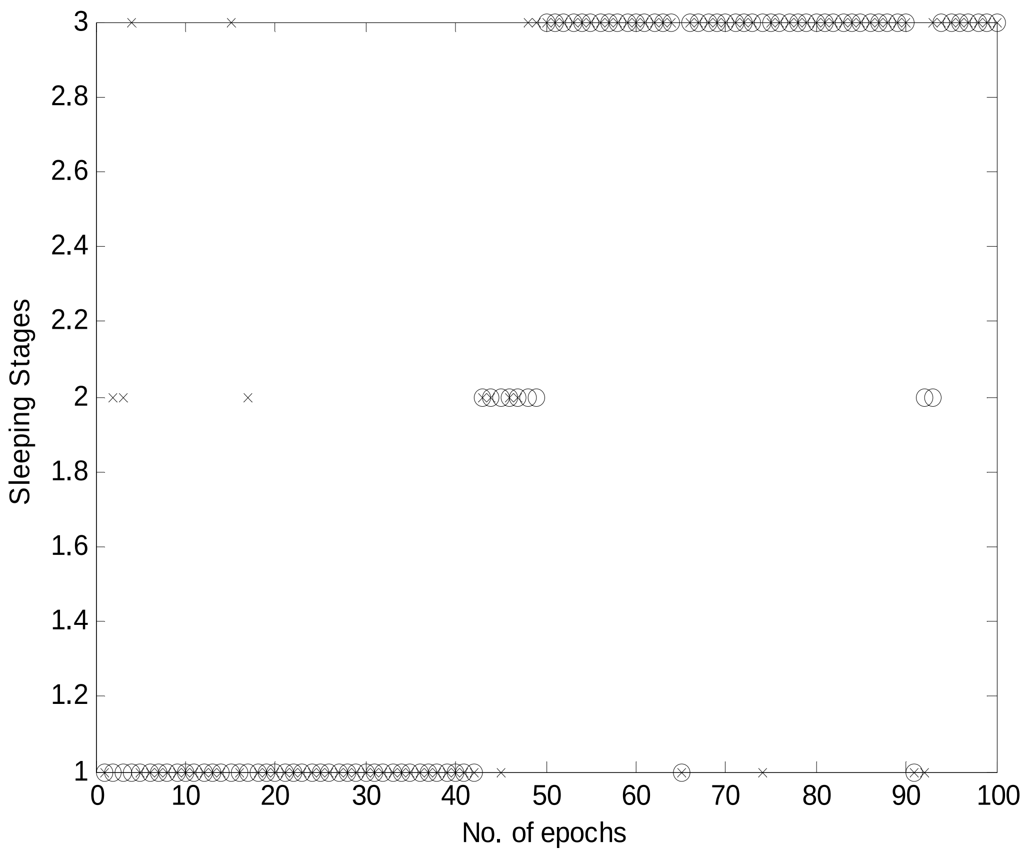


Figure 6-14: 10 neurons, 100 iterations, logsig, trainbfg, 89%, 100 epochs of data set and training set

6.4 Validation for the Accuracy of the Classification Result

Once the design of the classifier is complete, the goal is to determine how well it performs on the actual task. Previously, we applied a training set for the classifier, and a testing set (independent set) for testing the accuracy of classifier. This method of testing is known as generalization [21].

The statistical nature of the whole learning and test problem is taken into account if more than just one classifier is derived from the given sample set and is evaluated using more than just one test set [21]. With multiple training sets and multiple testing sets, it can gain information about the robustness of the results of classifier adaptation during classifier development.

A common statistical technique used to validate the classifier results is known as cross validation method. One typical cross validation method is called Jack-Knifing. The Jack-Knifing method also known as ‘leave one out’, is an iterative process in which one data is recruited each time for validation. A classifier is trained with all the data except one point for validation purpose. Then, another point is selected among the training set for validation while all the other points in the data are used for training the network. This iterative process repeats until all the data points in the group have been used for validation and the rest for training. In other words, with a total sample set of 100, all but one is used for learning and the remaining one for testing. This means 100 classifiers is created with 100 error rates. Taking the average of the 100-accuracy rates will serve as the true accuracy rate of the classifier. This ensures that the validation result is unbiased. The approach measures the ability of the classification adaptation rather than of one specific classifier.

The feed forward neural network classifier is tested with one hundred epochs of data. The resulting accuracy is 85%.

6.5 Summary

The feed-forward network has been analyzed in this chapter. Along with being the simplest network it was concluded as being the most effective one as well. Through analysis of this neural network, it was found that many parameters that could be adjusted to increase the accuracy of the network. The best training function for this purpose is the one based on Quasi Newton Algorithm called trainbfg, the best frequency range was [0 3; 4 7; 8 11; 12 38] Hz for Delta, Theta, Alpha and Beta frequency band waves respectively. The number of neurons in the hidden layer set at the value of 10 was found to be most optimal. Also, the network is trained best when the training set has the equal amount of data for each of the stages. Moreover, this technique, which is not very resource demanding could be efficiently incorporated into the Narcoleptic Assistive Device.

This classification method combined with the capabilities of Narcoleptic Assistive Device, would work well in making the lives of the narcoleptic affected people better.

Chapter 7

Conclusion

The main objective for the thesis is to develop a design of portable assistive device that facilitates the integration of narcoleptic patients to mainstream society. The narcolepsy assistive device performs real time monitoring of the EEG signal that can issue an alert to patients of probable narcoleptic attack. The device utilizes artificial intelligence algorithms to extract information to physicians so that they may provide accurate medical advice on medication dosage and activity planning.

This thesis discussed the selection of all the components of the Narcoleptic Device, which include Wet and Dry Electrode, Bio-amplifier, Micro-Controller, and Digital Signal Processor.

The thesis continued with detailed layout design of Digital Signal Processor. The Digital Signal Processor consists of three major sections, the Control Unit, Feature Extraction and Sleep Stage Classification.

Since sleep-stage classification is instrumental for the proper functioning of the Narcoleptic Assistive Device, three types of sleep stage classification of Aritificial Neural Networks has also been analyzed and optimized; Learning Vector Quantization, Probabilistic and Feed Forward

Neural Network were considered in this thesis. The optimized classifier of neural networks fulfils the final step in the development of Detective and Predictive models.

Based on the simulation results, it can be concluded that Feed Forward Neural Network is the best of the three.

Table 7-1: Classification Summary Table

Classifier	Accuracy of Classification
Learning Vector Quantization	70%
Probabilistic	79%
Feed Forward Neural Network	85%

Many researchers attempted to optimize the Neural Network classifier based on trial and error. Trial and error process is very time consuming. Instead, following proper steps will yield better results in a shorter period of time. During the optimization procedure of the Feed-Forward Neural Network classifier for sleep staging, six major adjustment steps were taken. They are:

- Number of layer in the Artificial Neural Network
- Number of neurons in the hidden layer
- Multiple Activation Functions/Training Functions
- Multiple Learning Functions
- Number of iteration for training epochs
- Frequency range of the sleep stage features (Alpha, Beta, Theta, Delta)

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Appendix A

The input layer accepts input signals from the outside world and redistribute them to all the neurons in the hidden layer which then detects the features.

In a feed forward network, the input vector, X, is propagated through a weight layer, V,

$$y_j(t) = f(net_j(t)) \tag{A.1}$$

$$net_j(t) = \sum_{i}^{n} Xi(t)Vji + \theta_j \tag{A.2}$$

where n is the number of inputs, θj is a bias, and f is an output function. Feed forward neural networks have been successfully used to solve problems that require the computation of a static function. Static functions are functions where the output depends only on the current input, not the previous inputs. **Figure A-1** shows the diagram of Feed Forward Neural Network.

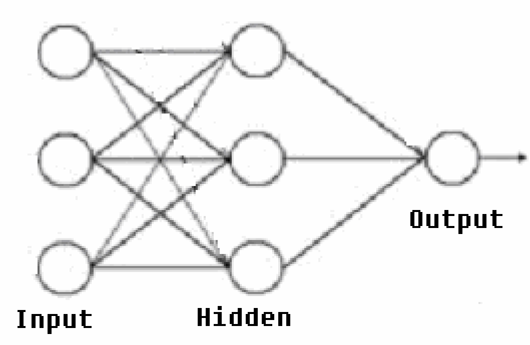

Figure A-1: Feed Forward Neural Network

Currently, this network is the most popular, effective and easy to apply for solving complex multi-layered networks. Moreover, a number of parameters are available which can be adjusted to increase the network's performance. Hence, this network was used for the purpose of this project.

The main components of this neural network include:

- **Weights -** These determine the strength of the signal. Any two layers of neurons communicate through a weight connection network. Each of the neurons can send a normalized signal to the other neurons in the network along connection wires. The signals that are passed are rescaled by synaptic weights, which determine the strength of the signal and in turn represent the features in the input patterns.

- **The summation function -** this determines the input for the next neuron. It is normally computed as the weighted sum of all inputs. In general, the total activity received by the i^{th} neuron can be given as:

$$A_i = \sum w_{ij} u_j \qquad \text{(A.3)}$$

Where w_{ij} is the weight for the connection from neuron j to neuron i and u_j represents the activity which is 1 if the j^{th} neuron is active and 0 if it is inactive.

- **Transfer function -** summation functions generates the sum and is passed to a transfer or activation function where the summed value and a threshold value are compared. This threshold value is generally non-linear and determines the output of the neuron.

- **Scaling and Limiting -** Scaling the result or limiting the result will optimize the result.

- **Output value -** Optimizing these 'training functions' is resulted from the optimal weigh. With the optimal weigh, the final results can be computed and the desired output is retrieved.

- **Error calculation and back propagation -** If the output value is different from the desired output, an error is calculated using an error function. This is then propagated backwards through the network from the output layer to the input layer.

Learning function - are functions that adjust the connection weights based on the algorithm based on the error propagated. Matlab has many inbuilt learning functions and these functions were utilized in the simulation. The most effective ones that were found to be based on Newton approach of approximating the Hessian matrix and the ones based on Jacobian [18][19].

Table A- 1: Activation Functions

Activation Functions	Explanation of each function:
Quasi Newton Algorithm	• A network training function that updates weight and bias values according to the BFGS quasi-Newton method.
Levenberg-Marquardt Backpropagation	• a network training function that updates weight and bias values according to Levenberg-Marquardt optimization.
Resilient Backpropagation	• a network training function that updates weight and bias values according to the resilient backpropagation algorithm (RPROP)
Scaled conjugate gradient back-propagation	• a network training function that updates weight and bias values according to the scaled conjugate gradient method

Appendix B

CHANGE IN NUMBER OF NEURONS IN THE HIDDEN LAYER

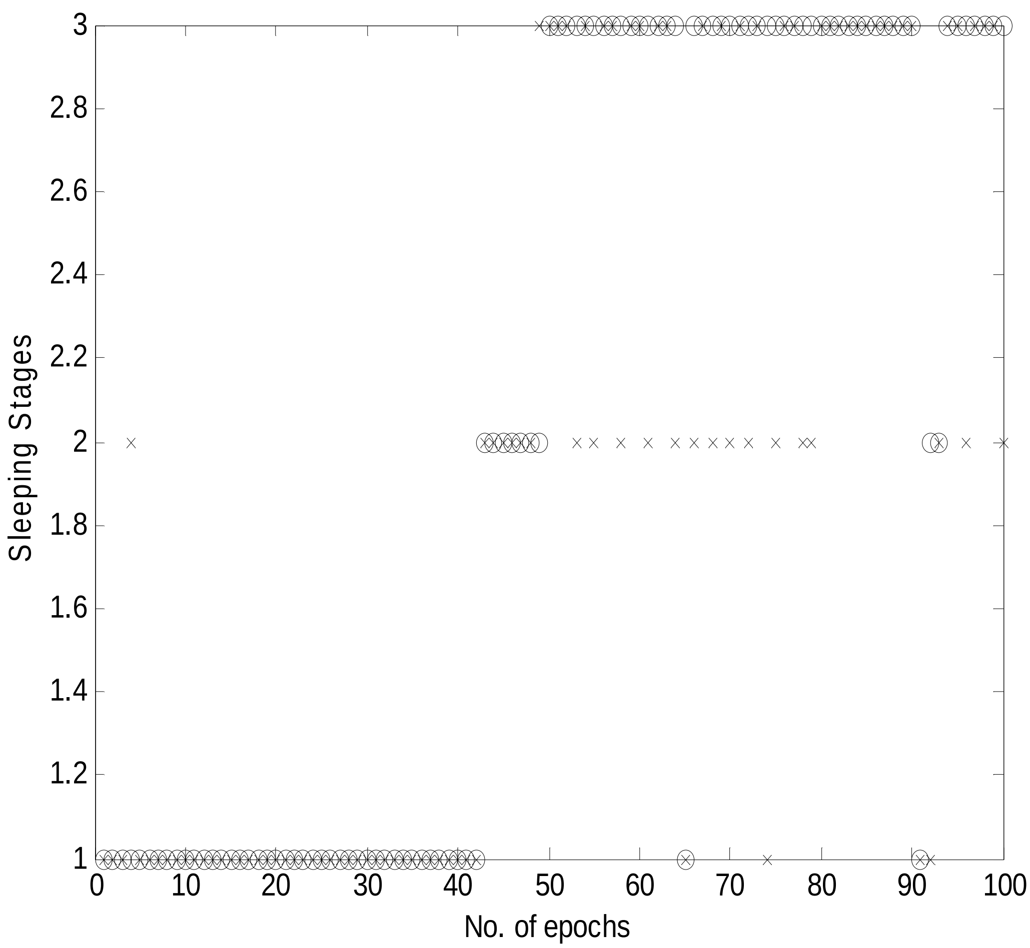

Figure B- 1: 15 neurons, 100 iterations, logsig, trainbfg, 82%, 100 epochs of data set and training set

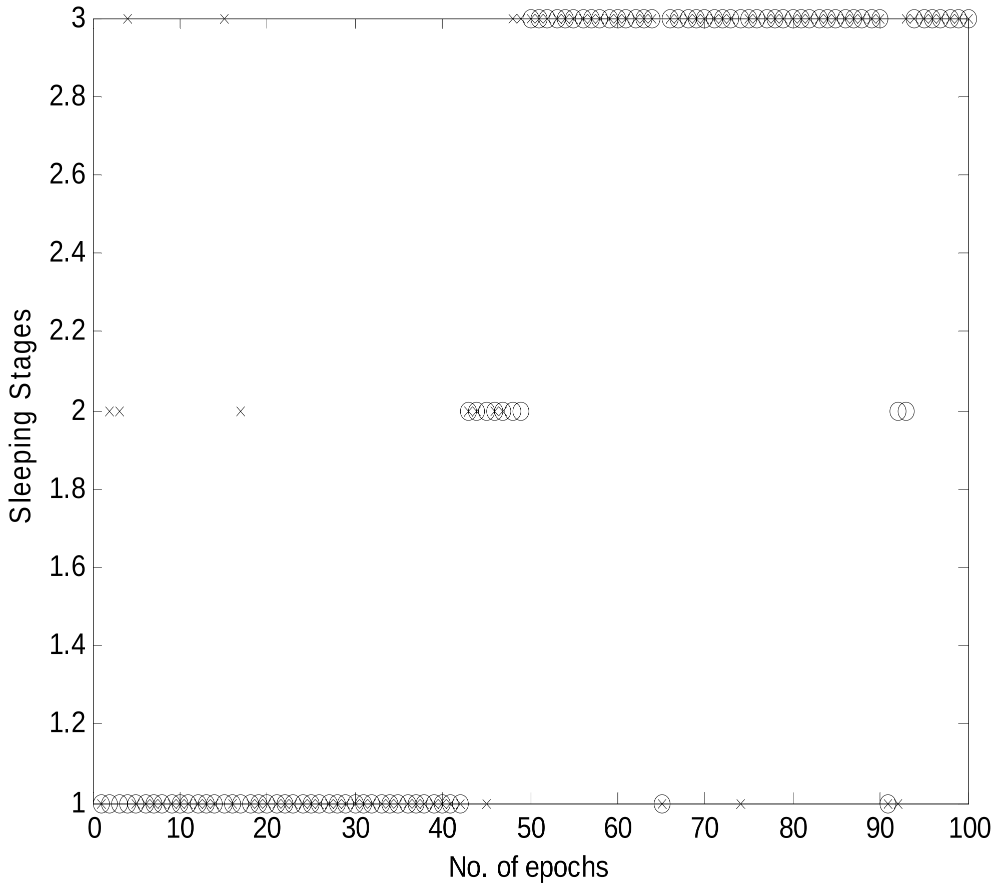

Figure B- 2:10 neurons, 100 iterations, logsig, trainbfg, 89%, 100 epochs of data set and training set

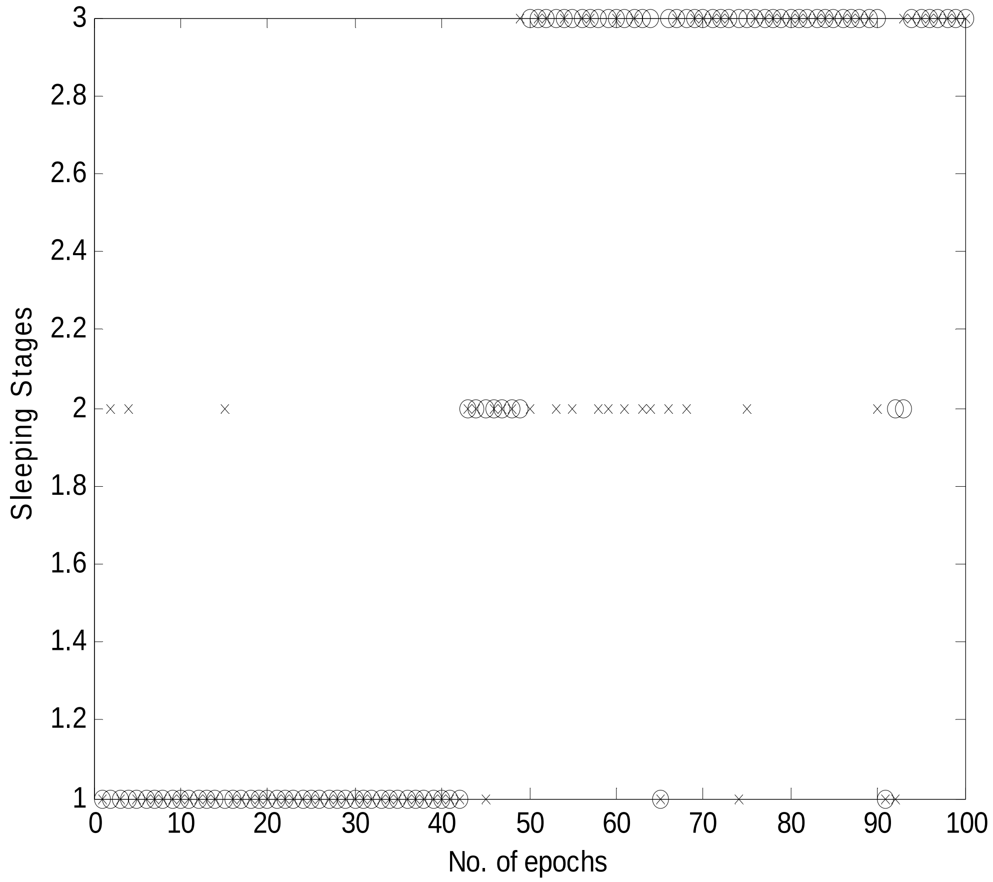

Figure B- 3: 6 neurons, 100 iterations, logsig, trainbfg, 80%, 100 epochs of data set and training set

- **CHANGE IN ACTIVATION FUNCTION**

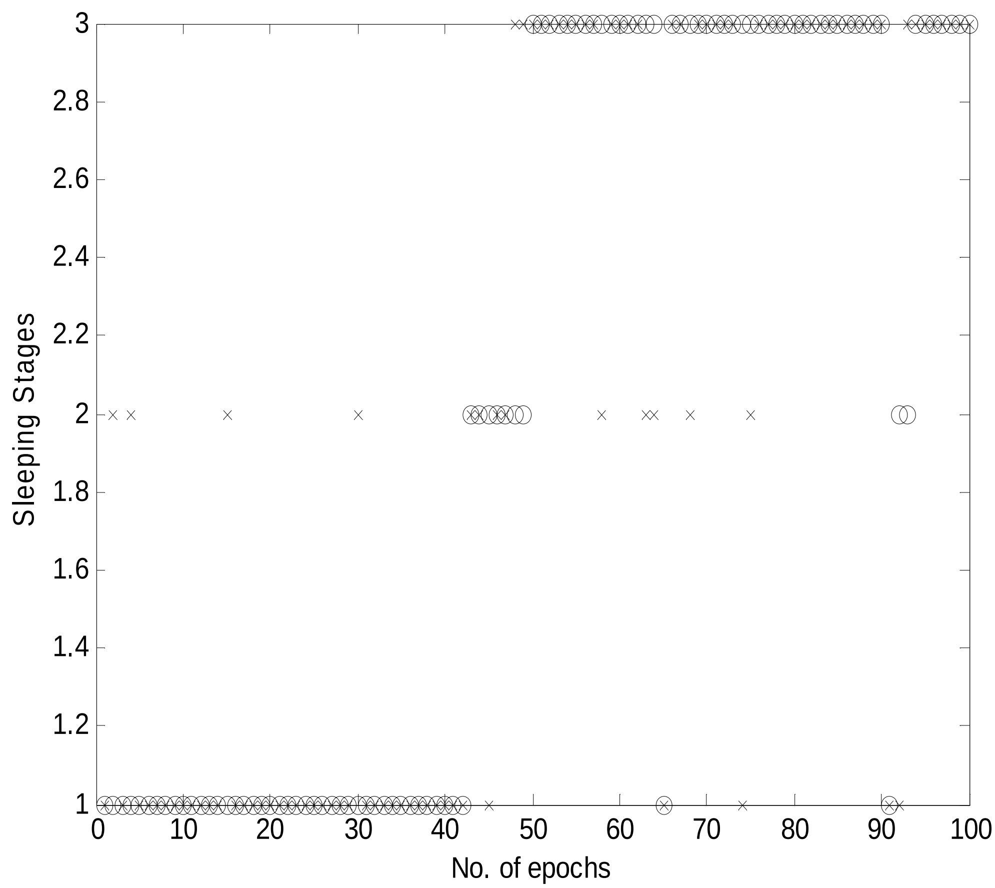

Figure B- 4: 10 neurons, 100 iterations, tansig, trainbfg, 85%, 100 epochs of data set and training set, slightly lower than logsig.

- **CHANGE IN LEARNING FUNCTIONS**

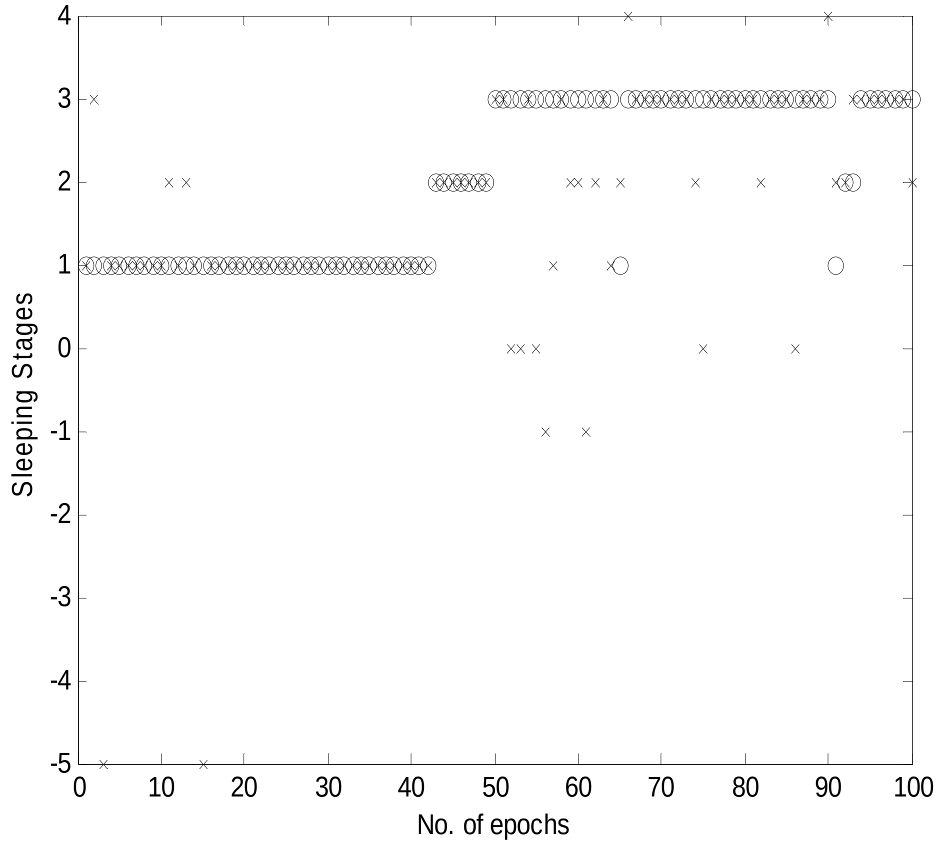

Figure B- 5: neurons, 100 iterations, logsig, trainlm, 75%, 100 epochs of data set and training set

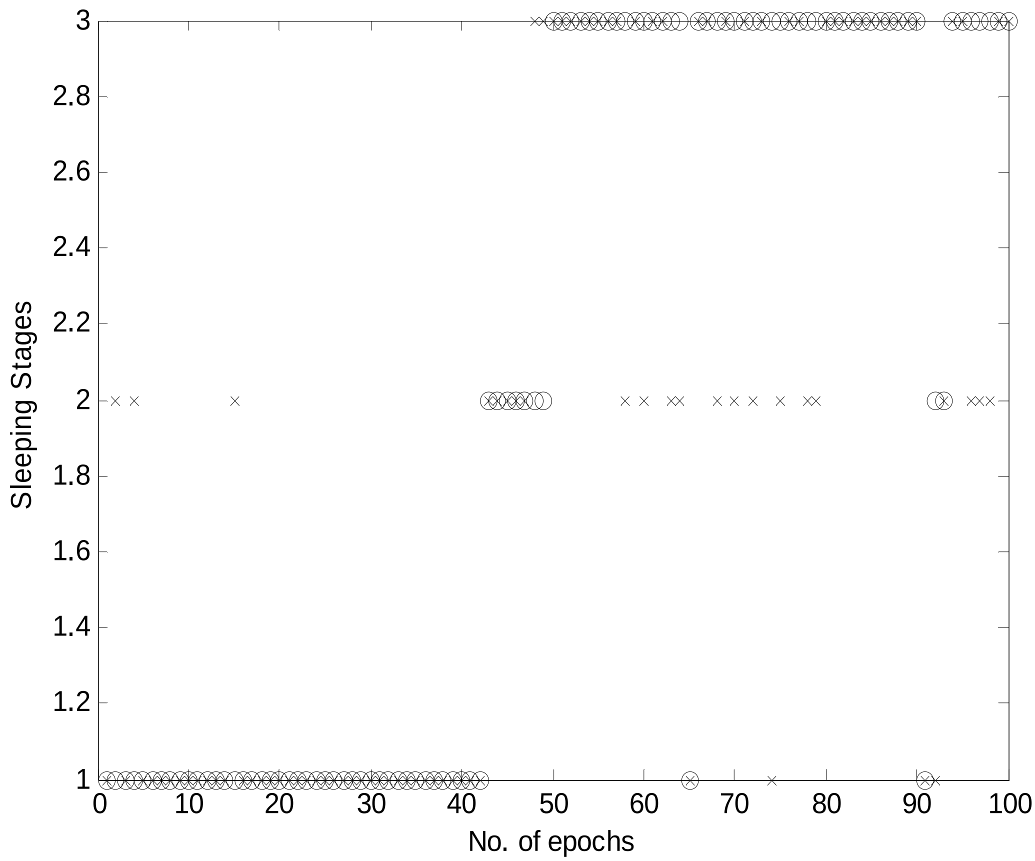

Figure B- 6:10 neurons, 100 iterations, logsig, traincgb, 80%, 100 epochs of data set and training set

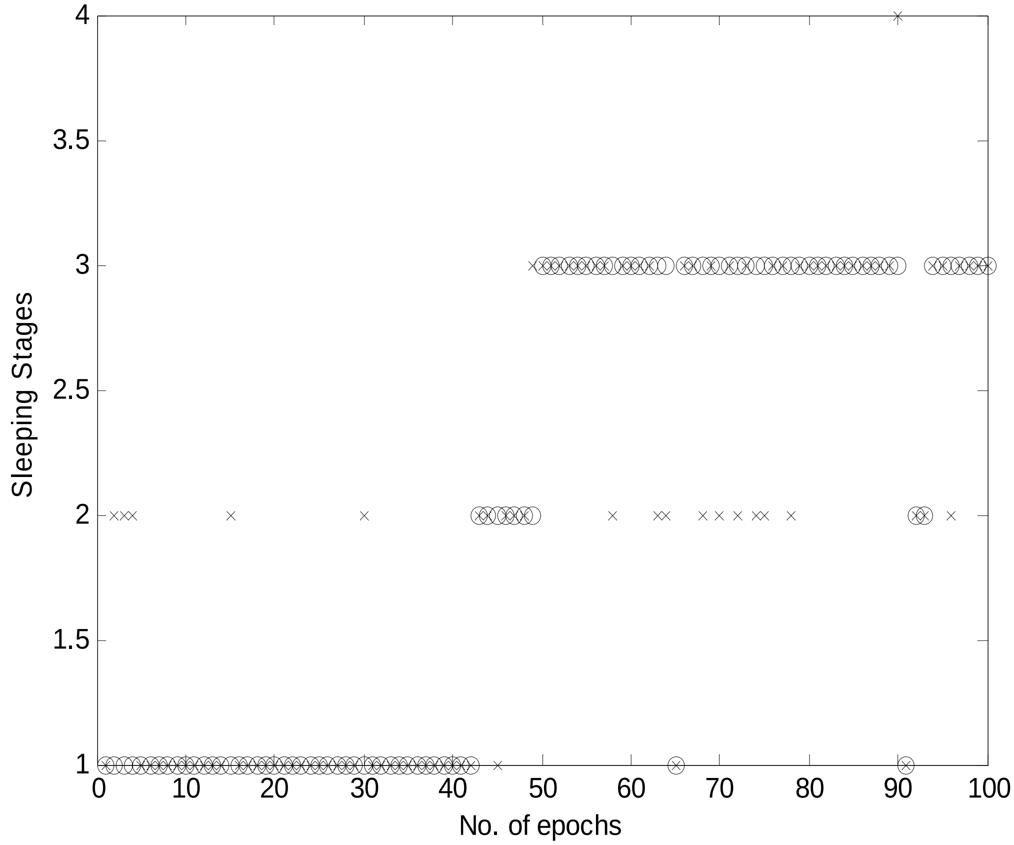

Figure B- 7:10 neurons, 100 iterations, logsig, trainrp, 82%, 100 epochs of data set and training set

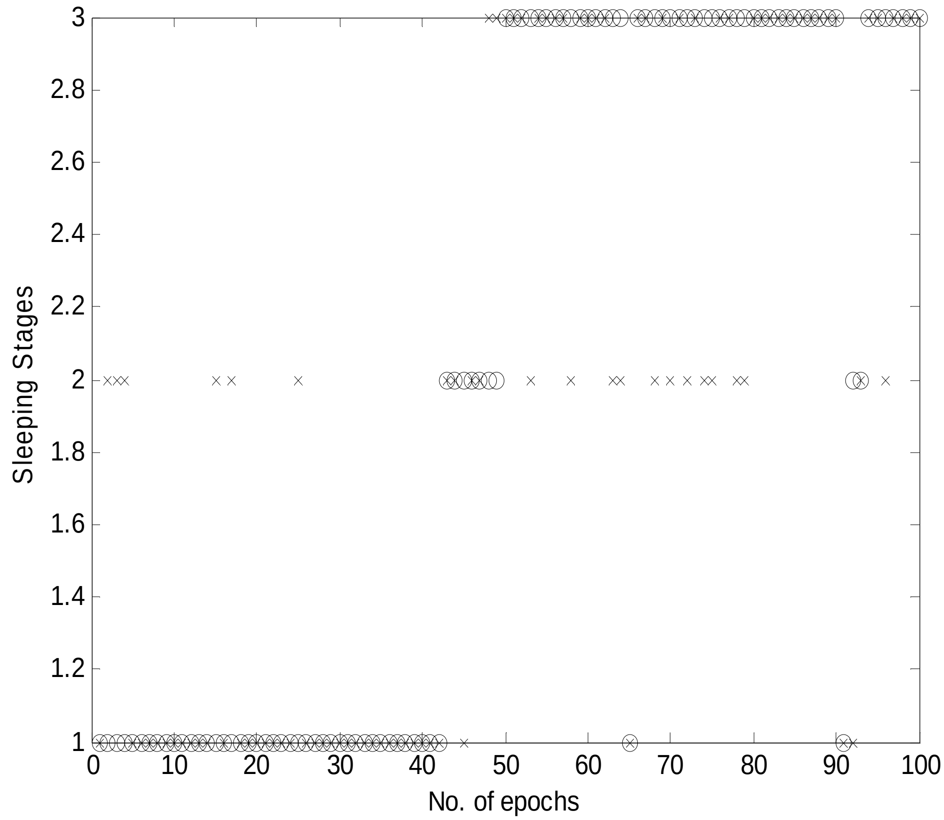

Figure B- 8:10 neurons, 100 iterations, logsig, trainscg, 78%, 100 epochs of data set and training set

- **CHANGE IN FREQUENCY RANGES WITH NEW TRAINING DATA**

Previous frequency range: [8 12; 12 40; 4 8; 0 4]

Lower frequency range: [8 11; 12 38; 4 7; 0 3]

10 neurons, 100 iterations, logsig, trainbfg, 80%, 100 epochs of data set and training set

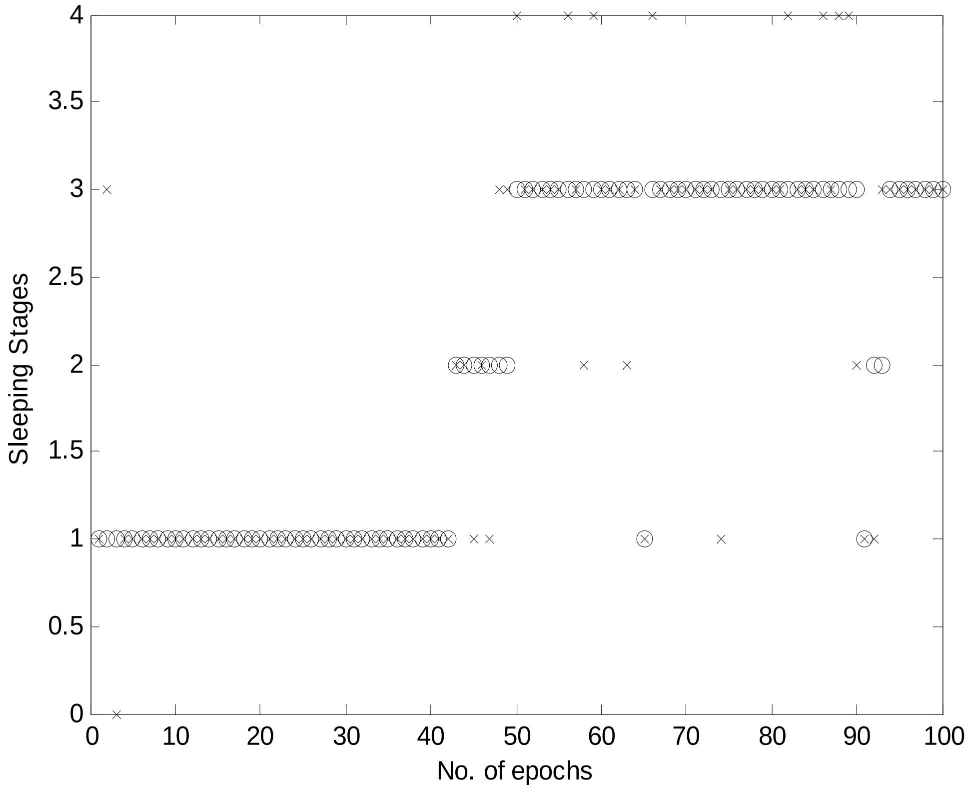

Figure B- 9: Higher frequency range: [9 13; 11 43; 4 10; 0 5]

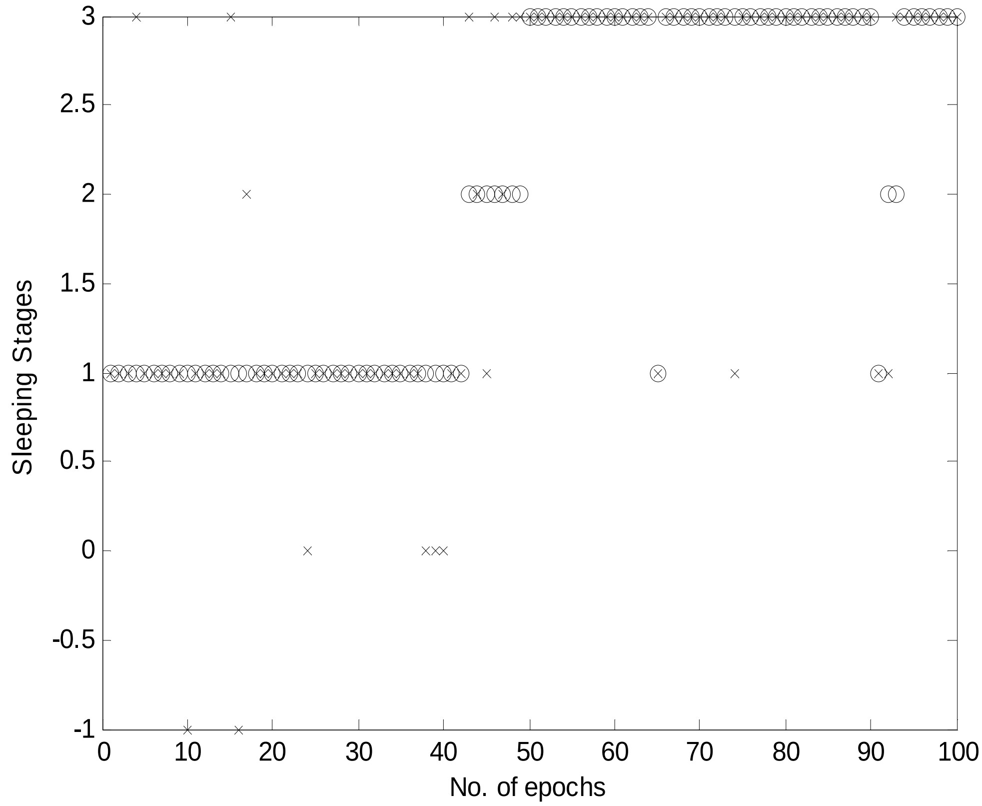

Figure B- 10: 10 neurons, 100 iterations, logsig, trainbfg, 83%, 100 epochs of data set and training set